Revolutionizing Public Policy and Management Teaching with Artificial Intelligence on Students' Analytical Skills Awareness and Risk Forecasting

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Abstract

In light of the global trend toward digital transformation, this study explores the integration of artificial intelligence into public policy and management education. It aims to evaluate the effects of AI technology on students' data analysis proficiency and risk forecasting capabilities, while also offering practical recommendations. With the rapid development of emerging technologies such as the Internet of Things, big data, cloud computing, and AI traditional teaching methods in public policy and management are increasingly inadequate in today's competitive and unpredictable market. This research introduces AI applications into the curriculum to enhance students' decision-making support and risk identification skills, thereby better aligning academic instruction with real-world industry demands. A survey was conducted with 216 students from the Department of public policy and management over a 16-week period (totaling 48 class sessions). The results demonstrated high internal consistency across all measured constructs, confirming the reliability and validity of the tools used. Moreover, correlation analysis revealed a significant positive relationship among AI application, analytical ability, and risk forecasting, supporting the idea that technological integration helps develop skills that improve risk assessment outcomes. Both structural equation modeling and nested model analyses confirmed that the overall theoretical model provided a good fit, effectively explaining the connection between enhanced learning outcomes and improved decision-making in the AI-based instructional experiment. In summary, the findings validate that the use of artificial intelligence can significantly boost students' analytical and risk prediction skills. This research offers robust empirical support for innovating public policy and management teaching methods. Moving forward, schools can use these insights to further refine curriculum design, promote instructor training and cross-department collaboration, and strengthen partnerships between academia and industry, ultimately driving a mutually beneficial evolution in both teaching practices and market requirements.

Keywords: Artificial Intelligence, Public Policy And Management, Analytical Ability, Risk Forecasting, Emotional Response

Introduction

Driven by the global wave of digital transformation, industries across the board face challenges in reinventing and modernizing their practices. In recent years, the rapid advancements in emerging technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence have spurred unprecedented changes in both traditional industries and the educational arena. This need is especially urgent in an era marked by unpredictable risks and intensifying market competition. Against this backdrop, leveraging new technologies to enhance the competence of corporate managers and sharpen students' abilities to analyze data and predict risks has emerged as a critical focus for both academic research and practical application. AI's strengths in automated data processing, pattern recognition, and large scale forecasting offer substantial support for decision-making processes, allowing students to gain deeper insights into complex public policy and management environments and associated risks. As a result, integrating AI into Analytical skills awareness in public policy and management education represents not only a technological breakthrough but also a vital step toward revitalizing traditional teaching methods and elevating educational quality.

Traditionally, public policy and management education has relied heavily on theoretical lectures and case studies, with instructor's predominantly driving classroom discourse and students passively receiving knowledge. However, as the complexity of market dynamics and public policy and management operations continues to grow, mere theoretical instruction has proven insufficient for addressing the multifaceted risks and uncertainties encountered in real world enterprises. Today's environment calls for a departure from old paradigms, emphasizing the cultivation of proactive learning, critical thinking, innovative problem-solving, and risk identification skills. AI-based technologies introduce a rich variety of application scenarios into public policy and management education. By harnessing big data and machine learning algorithms, students can engage in real time decision-making simulations and receive immediate feedback on how different choices impact company performance and market risk forecasts. Additionally, virtual simulations, intelligent tutoring systems, and interactive learning platforms provide hands on, practical tools that enable students to test theories in realistic settings and quickly adapt to market changes. With its significant capabilities in data processing, pattern recognition, and predictive analysis, AI empowers large scale and precise market trend evaluations, helping to uncover the hidden risks and opportunities within vast datasets.

Modern educational philosophies emphasize the seamless integration of technology with the humanities and social sciences a principle that is equally applicable in public policy and management training. While AI serves as a powerful technical tool, its application should not only emphasize scientific precision but also foster critical thinking, ethical awareness, and a sense of social responsibility among students. AI enhanced public policy and management education has the dual benefit of improving technical decision-making and guiding students to reflect on the broader social impacts and ethical dilemmas inherent in technology use. For example, while AI generated forecasts can significantly support risk predictions, they also necessitate that students understand and address issues such as algorithmic bias, data ethics, and privacy concerns. This study, therefore, aims to explore how to effectively blend technical expertise with humanistic values, ultimately preparing corporate leaders who excel in both analytical and ethical decision-making.

Although numerous studies both domestic and international have begun to explore AI applications in education, research specifically examining its use to boost students' analytical and risk forecasting skills in public policy and management remains limited. Internationally, scholars have primarily focused on technical implementations, such as developing big data based risk prediction models and designing intelligent decision support systems, using case studies and empirical research to highlight technological impacts. In contrast, studies in some regions have largely remained at the conceptual or demonstrative stage, with fewer evaluations of how these technologies enhance student learning and skill development. Moreover, as AI continues to evolve, so too do its educational applications. Early adaptive learning systems and later intelligent decision support tools may share some functionalities, yet they can differ significantly in practical usage. This evolution has spurred scholarly interest in integrating these technologies into a comprehensive teaching framework that not only reinforces theoretical learning but also hones practical capabilities thereby boosting students' proficiency in risk identification and analysis.

In summary, this study seeks to examine how the integration of AI in public policy and management education can simultaneously improve students' data analysis and risk prediction abilities while overcoming the shortcomings of traditional teaching methods. This research serves both as an empirical investigation of technological transformation and as an innovative endeavor in educational theory. It is hoped that through deep exploration, a standardized, practical, and forward thinking intelligent teaching model can be established one that ultimately elevates the overall competencies of Public policy and management professionals and provides solid intellectual and talent support for public policy and managements facing the challenges of risk management and decision-making.

Literature Review and Hypothesis

The Use of Artificial Intelligence in Public policy and management Education

Kaplan and Haenlein (2019) describe AI as a system that employs machine learning, natural language processing, and pattern recognition to mimic and in some cases, exceed human cognitive functions (Harishree and Jayapal, 2023). Although its range of applications is wide, in public policy and management the focus tends to be on decision support, predictive analytics, and automating routine processes. Zawacki Richter et al. (2019) characterize AI as a framework capable of simulating human decision-making, processing large volumes of data, and facilitating automated knowledge transfer (Holstein and Doroudi, 2022). They suggest that AI enabled educational platforms can dynamically tailor course content to match students' performance, thereby effectively bridging the gap between theory and practice especially in areas like risk management and decision simulations. Dwivedi et al. (2021) argue that because public policy and management integrates diverse areas such as marketing, finance, and operations, the interdisciplinary nature of AI makes it an ideal tool (Smuha, 2022). Embedding data-driven decision-making tools into management courses enables students to analyze trends and forecast risks using algorithmic methods, thus preparing them for proactive decision-making in the real world. Rane et al. (2024) highlight that AI serves as an automated data analysis platform, offering immediate feedback during instruction while adapting intelligently to individual learning behaviors. This adaptability is particularly valuable when traditional, static teaching methods cannot keep pace with rapidly changing market conditions. Shah et al. (2024) emphasize that AI's role extends beyond mere information delivery. By incorporating simulation experiments and virtual reality, AI helps students refine their decision-making skills through iterative learning, a process that is fundamental for mastering risk prediction and decision processes. According to Lohmann et al. (2019), AI systems empower students by placing them in simulated market environments where they can explore the impact of various decisions on corporate risk and performance in a controlled setting. Kiani (2024) note that, as part of decision support systems, AI leverages databases, predictive models, and decision tree techniques to assist students in extracting meaningful insights from complex data (Barazza, 2022). With AI driven simulation environments, public policy and management education can shift toward an experiential, case based learning approach that enhances students' ability to anticipate future risks. Aharonian et al. (2021) contend that integrating AI into data analysis and case study components of the curriculum allows students to observe firsthand how theoretical concepts are operationalized in practice (Alangari, 2024). This approach nurtures their ability to sift through vast amounts of data to identify key insights and make decisions based on robust predictive models, fostering sharper market awareness and risk management skills. Weber (2023) demonstrate that incorporating AI into public policy and management analytics courses significantly bolsters students' abilities in big data analysis, risk assessment, and simulation based decision-making effectively creating a synergy between academic theory and practical application. Agrawal et al. (2024) further illustrate that hands on experience with AI driven simulations enables students to directly engage in big data analysis and better appreciate how various decision variables interact in a public policy and management context.

Analytical Ability

Anastasi (2013) defines analytical ability as the systematic process of evaluating how information, arguments, and underlying assumptions relate to one another. Complementing this view, Renes and Brenk (2024). argue that Analytical skills awareness are not merely the accumulation of facts but are reflective capabilities that can be honed through targeted training, ultimately enhancing the quality of decision-making. Li et al. (2024) developed measures to assess an individual's capacity to pause and critically analyze when faced with intuitive errors, a test that gets to the heart of what analytical ability entails (Adi et al., 2024). In a similar vein, Pizlo (2022). describe a specific manifestation of Analytical skills awareness: the ability to recognize similarities between new and previously encountered situations, thereby transferring known solutions to novel problems. Bian (2022) suggest that much of the analytical process operates automatically and often beneath conscious awareness. Although individuals might not be able to explicitly describe their analytical methods, observable behaviors—like the time taken to make a decision or the choices they ultimately make offer insights into the depth of their analytical processing. Xiao et al. (2020) illustrate analytical ability through the lens of complex problem solving: breaking down intricate engineering challenges into smaller, manageable sub-problems, solving each one, and then integrating these solutions into a coherent whole. Van et al. (2022) recommend several strategies to foster analytical thinking, including logical reasoning, critical evaluation, evidence integration, and hypothesis testing, all of which contribute to building a robust analytical framework. Serrat (2021) notes that as individuals accumulate both educational experiences and practical knowledge, they evolve from relying solely on gut reactions to engaging in deeper analysis and reflection a transformative process that underpins the growth of Analytical skills awareness. Jahn and Cursio (2023) further describe analytical ability as a multi-step process that involves synthesizing, deducing, evaluating, and integrating information to arrive at well-founded conclusions. Finally, Boonsathirakul and Kerdsomboon (2021) view analytical ability as a critical dimension of overall critical thinking, comprising key components such as interpretation, reasoning, evaluation, inference, and self-regulation.

Risk Forecasting

Aven (2016) views risk forecasting as an integrated process that combines risk identification, analysis, and assessment (Sanguri and Mukherjee, 2021). Its essence lies in leveraging historical data, probabilistic models, and uncertainty analysis techniques to anticipate adverse events. Omenn and Eaton (2022) define risk forecasting as a procedure that employs mathematical, statistical, and computational models to estimate both the likelihood of occurrence and potential outcomes of events (Belly et al.,2023). According to Noriega et al. (2023), risk forecasting involves using historical financial records and behavioral indicators, along with statistical regression and machine learning approaches, to predict borrower default probabilities or other unfavorable events. Supriharyanti and Sukoco (2023) describe it as a systematic method that utilizes data mining, simulation, and predictive analysis techniques to quantify uncertainties in operational processes and forecast possible negative scenarios. Trucíos and Taylor (2023) argue that risk forecasting in the supply chain context involves integrating data from different stages and applying machine learning alongside statistical models to predict factors such as disruptions, delays, and demand fluctuations. Toumpourleka et al.(2021) frame risk forecasting as the process of using clinical data, patient records, and statistical tools to evaluate the risk of adverse health events, while Gaigall (2023) extend this idea to encompass the entire workflow—from data cleansing and feature extraction to algorithm training and ultimately predicting future patient health conditions using electronic health records (Molino and Sala, 2021). In a similar vein, Müller et al. (2024) define it as a process that uses probabilistic models like Bayesian networks to predict and assess security threats such as network attacks and data breaches. Vanegas and Mora Valencia (2025) focus on market risks, defining risk forecasting as predicting events such as market crashes or price volatility by employing historical market data, volatility indicators, and other macroeconomic variables through regression analyses and deep learning techniques (Apergis,2023). Lastly, Carter et al. (2021) present risk forecasting as the process of predicting the likelihood of future cardiovascular events by analyzing physiological parameters such as heart rate variability (HRV), along with signal processing and machine learning methods.

Impact of AI on Analytical Ability in Public policy and management Education

Kaplan and Haenlein (2019) suggest that AI platforms enable students to learn how to use data for reasoning and judgment even under uncertainty, thus markedly enhancing their Analytical skills awareness. Dwivedi et al. (2021) emphasize that the dynamic simulations and data visualization tools provided by AI significantly improve students' capacity to identify key factors and perform systematic analyses. Rane et al. (2024) note that AI platforms through the application of machine learning and data mining can adjust teaching strategies in real time based on students' behaviors during decision-making simulations, thereby crafting personalized learning pathways that boost their skills in data interpretation and risk prediction. Zawacki-Richter et al. (2019) observe that AI systems offer individualized feedback and automatically adapt learning content, which allows students to continuously refine their thinking and analytical processes. Such adaptive technologies help management students rapidly filter, synthesize, and analyze vital data amidst the complexities of market information. Shah et al. (2024) point out that AI driven simulated decision environments provide a safe space for students to experiment with various strategies repeatedly, affording them a thorough understanding of diverse public policy and management risks and opportunities. This iterative process nurtures their logical reasoning and critical evaluation skills across different scenarios, an essential component of analytical development. Lohmann et al. (2019) report that integrating AI-based simulation platforms into real-world public policy and management scenarios empowers students to conduct on-the-spot data analyses and risk evaluations, effectively transforming abstract theories into practical competencies while enhancing their ability to systematically dissect complex challenges. Kiani (2024) further argue that AI serves not only as a tool for data processing but also as a mechanism for constructing simulation decision trees and performing sensitivity analyses and risk assessments practices that sharpen students' quantitative and logical reasoning capabilities in intricate data environments. Additionally, Aharonian et al. (2021) highlight that AI powered intelligent teaching tools facilitate data-driven analysis and scenario simulations that bolster students' ability to process and interpret large volumes of complex information, thereby uncovering hidden patterns and advancing their Analytical skills awareness. Weber (2023) assert that by introducing AI technology, public policy and management education can more effectively cultivate students' proficiency in extracting actionable insights from extensive datasets and promote deeper logical reasoning and critical evaluation, which in turn refines their ability to discern risks and opportunities within public policy and management settings. Finally, Agrawal et al. (2024) demonstrate that AI can convert vast, complicated datasets into intuitive visualizations and predictive models, enabling students to grasp data patterns and market trends quickly while significantly enhancing their analytical, decision support, and risk assessment proficiencies. Based on the preceding literature, this study puts forth the following hypothesis:

Hypothesis 1: The integration of artificial intelligence into public policy and management education has a significant positive effect on analytical ability.

Impact of AI in Public policy and management Education on Risk Forecasting

Kaplan and Haenlein (2019) suggest that when students use AI systems in real-world or simulated settings, not only do they enhance the precision of their risk forecasts, but they also develop adaptive and decision-making mindsets—opening up new pathways for nurturing future corporate leaders. Dwivedi et al. (2021) observe that AI enabled, data-driven prediction methods make risk management training more reflective of real life challenges, thus better preparing students to confront risks in their future careers. Rane et al. (2024) further note that AI not only boosts the accuracy of risk predictions in management courses but also cultivates hands-on skills for effectively handling potential risks. Shah et al. (2024) have demonstrated that students immersed in AI enhanced learning environments significantly outperform those in traditional settings when it comes to tackling complex decision-making and risk management issues. Lohmann et al. (2019) report similar findings, showing that simulation training powered by AI markedly improves students' sensitivity to risk and their ability to adapt to changing conditions. Kiani (2024) introduce a conceptual framework centered on AI, where students can manipulate parameters in decision tree models to observe fluctuations in risk thereby learning how to make optimal decisions under uncertainty. Aharonian et al. (2021) argue that in addition to the technical aspects, AI integration in public policy and management education enhances students' overall risk management and early warning capabilities. Weber (2023) highlight that the use of AI not only increases the accuracy of risk forecasts but also accelerates the process through which students transform data analysis insights into practical decision-making skills (Cortés and Soriano, 2022). Furthermore, Agrawal et al. (2024) propose a classification framework for applying AI and big data analytics in public policy and management education, identifying risk forecasting as a key area that involves extracting latent risk indicators from raw data and enabling dynamic monitoring (Kouaissah and Hocine, 2021). Lastly, Zawacki-Richter et al. (2019) report that AI helps students grasp the risk assessment process better, allowing them to make more accurate judgments in complex decision-making scenarios. Based on these findings, this study proposes the following hypothesis:

Hypothesis 2: The integration of artificial intelligence into public policy and management education has a significant positive impact on risk forecasting.

Impact of Analytical Ability on Risk Forecasting

Li et al. (2024) contends that a higher level of analytical ability helps individuals overcome intuitive biases, leading to more precise and reasonable risk forecasts. In the view of Renes and Brenk (2024)., advanced Analytical skills awareness enable individuals to systematically evaluate various possibilities in uncertain environments, thereby reducing the likelihood of making decisions based solely on intuition. Toplak (2022) emphasize that strong Analytical skills awareness are crucial in complex risk scenarios, as individuals with these skills are better able to sift through vast amounts of data, extract key details, and conduct in-depth analyses that lead to reliable risk predictions. Kumar and Singh (2024) add that bolstering analytical capabilities encourages individuals to rely more on logical reasoning rather than simple heuristics, which in turn improves the accuracy of risk assessments. Berent et al. (2020) argues that when faced with uncertainty, individuals with heightened analytical ability are more inclined to move beyond immediate intuitive responses and adopt rigorous, data-driven approaches to evaluate risk. Kerzner (2023) also note that well-developed Analytical skills awareness allow for a flexible interplay between heuristic and analytical thinking, enabling the use of complex mathematical models and statistical methods when forecasting risk is critical. According to Mascio and Fabozzi (2019), individuals with strong analytical abilities tend to adopt more refined strategies for processing and interpreting detailed information, which helps them differentiate between various levels of risk and make better-informed judgments. Hertwig and Erev (2009) further suggest that enhanced Analytical skills awareness allow individuals to compensate for the lack of experiential data through logical reasoning, resulting in more accurate risk predictions. Serrano et al. (2024) finds that individuals with higher analytical capabilities typically assess their skills and associated risks more objectively, leading to more cautious and well-reasoned forecasts. Shrader-Frechette (2023) argue that strong Analytical skills awareness enable individuals to maintain rationality even in the face of emotional reactions, thus making better use of data and statistical models for risk prediction. While emotions undoubtedly influence risk perception, a systematic, analytical approach can help mitigate their disruptive effects and yield more objective outcomes. From this review, the following hypothesis is proposed:

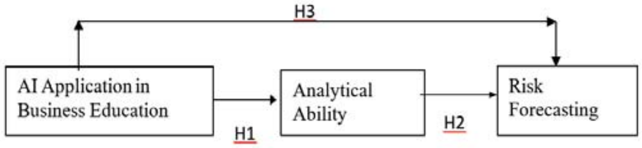
Hypothesis 3: Analytical ability has a significant positive effect on risk forecasting.

Methodology

Conceptual Framework of This Study

Based on the literature review presented above, this study's conceptual framework was developed (see Figure 1). The framework explores the relationships among the use of artificial intelligence in public policy and management education, analytical ability, and risk forecasting.

Figure 1: Conceptual Framework Diagram



Measurement of Research Variables

1. AI Application in Public policy and management Education

This study adopts the definition by Kaplan and Haenlein (2019), who describe AI as a technology that supports decision-making through data processing, natural language processing, and simulated decision-making. In the context of public policy and management education, three primary dimensions are measured:

a. Perceived Usefulness: This dimension gauges the extent to which respondents believe that using the AI system improves their learning outcomes, risk forecasting, and decision support.

b. Perceived Ease-of-Use: This reflects whether users find the system straightforward and hassle-free to operate.

c. Behavioral Intention to Use: This dimension assesses the willingness of both students and educators to continue using the AI system in future courses or teaching sessions.

2. Analytical Ability

Drawing on Mascarenhas et al. (2023) and his exploration of critical thinking in public policy and management education, this study focuses on analytical ability as it pertains to evaluation and argument construction. The key dimensions measured are:

a. Data Integration Ability: In a public policy and management environment, the ability to synthesize and summarize diverse pieces of information into cohesive insights is crucial.

b. Logical Judgment: This dimension measures whether individuals maintain consistent and coherent evaluations across similar public policy and management scenarios by applying rigorous logical principles to prevent contradictory conclusions.

c. Reflection and Regulation: This examines the individual's propensity to critically review and adjust their initial judgments. It assesses whether one actively re-evaluates their thought processes to avoid impulsive decisions or logical biases.

3. Risk Forecasting

Building on the theoretical framework proposed by Shrader-Frechette (2023) this study conceptualizes risk perception as comprising both rational analysis and emotional response. Its core dimensions are:

a. Rational Analysis: This facet emphasizes that individuals perform systematic cognitive evaluations of risk using logical reasoning, statistical probability, cost-benefit analysis, and conscious assessments of the severity of potential outcomes (e.g., expected losses, injury severity).

b. Emotional Response: This dimension captures the instinctive emotional reactions or feelings elicited when evaluating risk, such as fear, anxiety, discomfort, or aversion.

Experimental Design and Participants

This study examines the use of artificial intelligence in public policy and management education by exploring participants' views on AI integration, analytical ability, and risk forecasting. A total of 216 university students from the department of public policy and management in Taiwan were recruited for the experiment, consisting of 92 males and 124 females. The experimental procedure began with a brief orientation to explain the study's objectives. Participants then took part in a 16-week experiment encompassing 48 class sessions, after which they completed a questionnaire. The questionnaire was divided into sections covering demographic information, AI application in public policy and management education, evaluation of analytical ability, and risk forecasting assessment. A five-point Likert scale was used to measure responses.

Analysis and Discussion

Factor Analysis

The results of the factor analysis are summarized in Table 1.

For the "AI Application in public policy and management Education" scale, the factor analysis extracted three factors. The first factor is "Perceived Usefulness" (eigenvalue = 3.216, α = 0.83), the second is "Perceived Ease-of-Use" (eigenvalue = 2.155, α = 0.86), and the third is "Behavioral Intention" (eigenvalue = 1.833, α = 0.88). Together, these three factors explain 78.266% of the total variance.

For the "Analytical Ability" scale, three factors were extracted as well. The first factor is "Data Integration Ability" (eigenvalue = 2.463, α = 0.89), the second is "Logical Judgment" (eigenvalue = 2.057, α = 0.90), and the third is "Reflection and Regulation" (eigenvalue = 1.724, α = 0.87). These factors collectively account for 80.679% of the total variance.

For the "Risk Forecasting" scale, the factor analysis identified two factors. The first is "Rational Analysis" (eigenvalue = 4.035, α = 0.91) and the second is "Emotional Response" (eigenvalue = 3.211, α = 0.92). Together, these two factors explain 85.233% of the total variance.

Table1: Factor Analysis Summary

Variable	Factor Dimension	Eigenvalue	α	Cumulative Explained Variance (%)
AI Application in Public policy and management Education	Perceived Usefulness	3.216	0.83	78.266
	Perceived Ease-of-Use	2.155	0.86	
	Behavioral Intention	1.833	0.88	
Analytical Ability Awareness	Data Integration Ability	2.463	0.89	80.679
	Logical Judgment	2.057	0.90	
	Reflection and Regulation	1.724	0.87	
Risk Forecasting	Rational Analysis	4.035	0.91	85.233
	Emotional Response	3.211	0.92	

Correlation Analysis

As shown in Table 2, there are significant correlations among AI Application in public policy and management Education, Analytical Ability, and Risk Forecasting. These findings suggest that there may be a degree of linear overlap among the study constructs. Scholars recommend that if such an issue arises, nested model analysis can be employed to address it. Moreover, the significant correlations between the constructs align with and support the hypotheses proposed by the researcher.

Table 2: Correlation Analysis

Research Construct	α	AI Application in Public policy and management Education	Analytical Ability Awareness	Risk Forecasting
AI Application in Public policy and management Education	0.85			
Analytical Ability Awareness	0.86	0.30**		
Risk Forecasting	0.90	0.34**	0.42**	

Note: **p < 0.01.

Theoretical Model Exploration

In the overall presentation of our results, significant path coefficients are denoted by solid lines, while non-significant ones are shown as dashed lines. As observed, all path coefficients among the variables are significant, indicating that they meet the standards for convergent validity and fulfill the basic requirements of the analysis model. Furthermore, the model fit indices GFI = 0.958, AGFI = 0.931, RMSEA = 0.03, and CFI = 0.923 confirm that our theoretical model is well-fitted, thereby affirming both its theoretical soundness and validity.

Hypothesis Testing

For hypothesis testing, a nested model approach was employed using chi-square difference tests. Since each nested model differs from the theoretical model by one degree of freedom, a significant chi-square difference ($\Delta\chi^2$) indicates that the path coefficient, which was constrained to zero in the nested model, is indeed significant. The results reveal that the model is significant. Detailed outcomes of the nested model analysis are presented in Table 3 while the hypothesis testing results can be found in Table 4.

Table 3: Nested Model Analysis Summary

Model	χ^2	$\Delta\chi^2$	GFI	CFI	RMSEA
Theoretical Model	215.83		0.958	0.923	0.03
Model 1: Hypothesis Test	219.05	3.22*	0.958	0.923	0.03
Model 2: Hypothesis Test	222.56	3.51*	0.958	0.923	0.03
Model 3: Hypothesis Test	226.69	4.13*	0.958	0.923	0.03

Note: * p < 0.05

Table 4: Hypothesis Testing Summary

Research Hypothesis	Correlation Sign	Empirical Result	p-value	Outcome
Hypothesis 1	+	0.322	0.00	Supported
Hypothesis 2	+	0.334	0.00	Supported
Hypothesis 3	+	0.427	0.00	Supported

Discussion

This study examined three major dimensions: the use of AI in bsiness education, analytical ability, and risk forecasting. We employed factor analysis, correlation analysis, and theoretical model validation to explore these constructs. From the correlation analysis, it is evident that AI application, analytical ability, and risk forecasting are all significantly and positively correlated. Specifically, the correlation between analytical ability and risk forecasting is 0.42 and that between AI application and risk forecasting is

0.34 (both at $P < 0.01$). In addition, the correlation between AI application and analytical ability is 0.30, which is also statistically significant. These results suggest that as the application of AI in public policy and management education increases, the resulting enhancement of Analytical skills awareness may further facilitate the integration of rational and emotional components in risk judgment. In other words, a learning environment with a high degree of AI usage can boost users' capacity to synthesize data and information, thereby influencing their rational and emotional responses when encountering risk.

Given the degree of linear overlap among the research constructs, our research team recommends using a nested model analysis in future data analyses. This approach can help further disentangle the interactive effects among the constructs, reduce collinearity issues, and examine any potential mediating or moderating effects. As shown in Table 3, the significant chi-square differences among the nested models—together with excellent fit indices for the theoretical model (GFI = 0.958, CFI = 0.923, RMSEA = 0.03) further support the convergent and discriminant validity of our measurement tools. This indicates that not only are the specified path coefficients statistically significant, but the constructs also possess sufficient explanatory power, which is consistent with our initial hypotheses.

In testing our hypotheses (see Table 4), all three hypotheses demonstrated positive relationships with correlation coefficients of 0.322, 0.334, and 0.427 respectively (all $P < 0.01$). These findings further confirm the strong link among AI application, analytical ability, and risk forecasting. Essentially, when organizations leverage AI technologies and focus on cultivating analytical abilities, this can lead to improved rational judgments and emotional responses regarding risk, thereby promoting positive technology adoption and decision-making behaviors. This outcome aligns with the conclusions drawn from existing literature on risk assessment and decision support, and it offers empirical support for the application of digital technology within public policy and management education.

Overall, the multi-factor structure employed in our scale construction appears both appropriate and theoretically sound, with the relationships among the constructs closely matching theoretical predictions. The model validation process showed that all path coefficients were statistically significant and the overall model fit was excellent, demonstrating that our framework has high explanatory and predictive power. These results indicate that stable and reliable measurement indicators can be achieved for AI application, analytical ability, and risk forecasting findings that offer important theoretical and practical contributions for advancing digital transformation in public policy and management education and shaping risk management strategies.

Furthermore, the observed positive effects reflected by the correlation coefficients and nested model analysis suggest that there are potential interaction effects among the variables. This observation underscores the need for future research to introduce moderating variables (such as organizational size, industry type, etc.) or mediating factors to delve deeper into the mechanisms underlying these relationships. Future studies could compare different industries or management levels to investigate whether structural differences exist for instance, determining if the positive association between AI application and analytical ability is even more pronounced in sectors with higher technology acceptance, or if the emotional component of risk forecasting plays a more significant role in industries characterized by high uncertainty.

In summary, the multidimensional structure proposed in this study effectively captures the real-world cognitive and behavioral patterns of corporate managers as they navigate digital transformation and risk challenges. This discussion not only validates the theoretical constructs underpinning the research but also provides empirical evidence to support the integration of AI in public policy and management education, the development of robust Analytical skills awareness, and the accurate forecasting of risk. The findings offer valuable insights for both academia and industry, providing a comprehensive measurement tool for further cross-national, cross-industry comparisons under varying organizational, industrial, and cultural contexts, and revealing additional potential moderating factors. Moreover, the excellent model fit indicated by our structural equation modeling not only underscores the deep interrelationships among the constructs but also offers concrete guidance for practitioners when designing training programs or risk management strategies. Therefore, in pursuing digital transformation or refining decision-making processes, it is crucial to enhance the application of AI and to bolster analytical abilities, thereby enabling more effective risk prediction and response.

In conclusion, this discussion illuminates the important roles of the studied constructs in a digital management environment and demonstrates the benefits of integrating both cognitive and affective dimensions in risk forecasting. The results offer significant theoretical and practical implications for how organizations can effectively integrate AI, enhance analytical capabilities, and elevate risk assessment standards during decision-making processes.

Conclusion

This study validated a theoretical model through factor analysis, structural equation modeling, and nested model analysis, focusing on three main dimensions: AI application in public policy and management education (comprising perceived usefulness, perceived ease-of-use, and behavioral intention), analytical ability (including data integration ability, logical judgment, and reflection and regulation), and risk forecasting (encompassing rational analysis and emotional response). The overall results show that each dimension demonstrates high internal consistency (with Cronbach's α values above 0.80) and cumulative explained variances of 78.27%, 80.68%, and 85.23%, respectively strong evidence of the measurement tool's stability and validity. Moreover, the significant positive relationships among these dimensions, as confirmed by the model's path coefficients and fit indices (GFI, AGFI, CFI, RMSEA), indicate that the theoretical model effectively explains the internal dynamics between students' learning outcomes and their enhanced decision-making abilities observed during the AI teaching experiment.

In the AI application dimension, students rated both the perceived usefulness and ease-of-use of AI technology in public policy and management education very highly. This suggests that when instructors incorporate AI technologies in the classroom and provide ample practical cases and hands-on activities, students quickly recognize the practical value of these tools in decision support, data integration, and problem solving. The significant boost in behavioral intention further indicates that, beyond active engagement in class, students are inclined to adopt AI technology as a decision-support tool in their future careers. These findings are consistent with the Technology Acceptance Model (TAM), which emphasizes the roles of perceived usefulness and ease-of-use in shaping behavioral intention, thereby providing empirical support for digital transformation in public policy and management education.

Regarding analytical ability, this study subdivided the construct into three dimensions: data integration ability, logical judgment, and reflection and regulation. The empirical results reveal that after participating in the AI assisted teaching experiment, students' data integration ability improved significantly. This improvement means that when confronted with large volumes of diverse information, students can quickly identify key points and synthesize data to form a systematic understanding. The logical judgment dimension reflects their ability to use reasoning and Analytical skills awareness when addressing complex situations, whereas reflection and regulation show that students can review and adjust their thought processes in light of real outcomes. This combination of data-driven analysis and continuous self-reflection is vital for developing future managers who can navigate uncertain market conditions and high-risk decision-making scenarios a capability that holds considerable long-term practical value in today's rapidly changing digital landscape.

The risk forecasting dimension was explored from both rational analysis and emotional response perspectives. The data indicate that when making risk judgments, students rely not only on objective data and logical reasoning but also on their emotional reactions such as intuitive fear or anxiety which significantly influence their risk assessments. This dual perspective supports Shrader-Frechette (2023) "risk as analysis and risk as feelings" theory, suggesting that decision-makers in corporate settings must account for emotional factors when controlling risks and making decisions. For educational institutions, this finding underscores the need to design AI assisted decision simulation activities that balance rational and emotional inputs. Such an approach ensures that while students make data-based scientific judgments, they also learn to manage the emotional fluctuations and irrational tendencies that can arise during decision-making.

Overall, the experimental results reveal a positive cascade effect among the three dimensions, confirming the causal chain of "technology application → capability cultivation → risk judgment." In practical terms, the AI teaching experiment not only enhanced students' acceptance of advanced technology but also, in the short term, significantly boosted their data processing and decision-making skills an outcome that ultimately contributes to more comprehensive risk forecasting and integrated thinking. The excellent model fit as indicated by indices such as GFI = 0.958, CFI = 0.923, and RMSEA = 0.03 further substantiates the statistical significance of all path coefficients and provides robust empirical support for the effectiveness and validity of the school-based experimental model.

Furthermore, this study demonstrates the strengths of a cross-disciplinary learning approach within a campus setting. By leveraging an AI experimental platform that deeply integrates information technology, data analytics, and public policy and management content, the teaching model enables students not only to acquire technical knowledge but also to apply that knowledge to resolve real management problems. This practice-oriented approach not only cultivates practical skills for the workplace but also shows significant potential in stimulating innovative thinking and nurturing a data-driven decision-making culture. In today's global push toward digital transformation, such experiential teaching experiments can serve as a key catalyst for curriculum reform and quality enhancement in higher education.

From a practical standpoint, the study offers concrete recommendations for public policy and management education. Schools can use these findings to optimize curriculum design and teaching content for example, by incorporating more case-based exercises and simulated decision-making drills to enhance students' risk judgment and decision-support capabilities. Moreover, establishing industry-academia-research alliances can accelerate technology transfer and ensure that graduates are well-aligned with industry needs. This collaborative model not only supports corporate digital transformation but also provides valuable empirical evidence to guide policy-making and resource allocation by governments and educational institutions. The results of this study emphasize the importance of addressing both the rational and emotional components in AI application experiments. In the future, educational institutions should explore more finely tuned simulation scenarios that help students manage their emotional responses while engaging in data analysis and risk forecasting. Doing so will improve students' learning outcomes and professional competitiveness, and offer critical insights for enterprises seeking to craft more effective decision-making strategies in increasingly complex market environments.

In summary, this study set against the backdrop of a school-based experiment in applying AI in public policy and management education—deeply examined the interrelationships among AI application, analytical ability, and risk forecasting, and successfully established a theoretical model with strong explanatory and predictive power. The model not only confirms the positive relationship between technology application and capability development but also highlights the significant role of emotional factors in risk judgment. These findings enrich theoretical research and provide a reliable basis for innovations in public policy and management education, digital transformation, and decision-support system design. Future research should continue to refine this experimental model through cross-disciplinary collaboration, long-term tracking, and the integration of multiple variables, with the ultimate goal of achieving a mutually beneficial development between educational institutions and industry needs.

Ultimately, the conclusion underscores the pivotal role of these dimensions in a digital management environment and demonstrates the benefits of integrating both cognitive and emotional aspects in risk forecasting. The insights gained from this study offer valuable guidance for how organizations can effectively integrate AI applications, enhance analytical capabilities, and improve risk assessment processes implications that are both theoretically significant and practically relevant.

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