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Decision-making Algorithms Based on Artificial Intelligence

Jianlei Qian,[1*] Kun Wang,[2] and Zonglin Li[2]

[1]Cybersecurity and Informatization Office, Shandong University of Finance and Economics, Jinan 250014, China
[2]Shandong University of Finance and Economics, Jinan 250014, China

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Advancements in AI technologies have transformed decision-making processes across various industries. However, effective AI technology usage necessitates an understanding of the capabilities of algorithms. Therefore, we explored how the effectiveness of AI analytics enhances decision-making capabilities. A structured questionnaire survey was conducted with 91 professionals across industries to assess user experience with AI analytics, perception of its effectiveness in decision-making, impact on decision-making effectiveness, and implementation challenges. The perception of its effectiveness scored 2.69, user experience with AI analytics scored 3.09, and decision-making effectiveness scored 3.73 on average. Challenges for the implementation of AI analytics showed a significant positive correlation with the perception of effectiveness in decision-making. Although the potential of AI analytics is widely recognized, challenges in addressing its implementation must be addressed. The findings of this study provide a basis for understanding how to effectively utilize AI technologies. The importance of integrating human expertise must be emphasized to enhance decision-making capability with the help of AI technologies.

1. Introduction

Sensor technology has enhanced the decision-making ability of companies by providing real-time data and data analytics. Sensors are used in manufacturing to monitor equipment health, detect anomalies, and predict failures. They are also used in logistics and workplace environmental improvement by tracking inventory levels, shipment conditions, and delivery times, and monitoring workplace conditions to comply with safety standards and reduce the risk of accidents.[1,2] Sensors with AI technology are also used for service industries for healthcare diagnostics, financial forecasting, and autonomous driving. The data collected is used for making timely and effective decisions, which are essential to help companies remain profitable and pursue sustainable development.

AI has been applied to decision-making processes based on sensor data. AI simulates human intelligence processes such as learning, reasoning, problem-solving, perception, and language processing to process large amounts of data, obtain information, and make reasonable decisions

*Corresponding author: e-mail: qianjl@sdufe.edu.cn
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with unprecedented speed and exactness.[3] With increasing dependence on data-based decision-making, AI analytics becomes essential in tackling complex challenges.[4]

Since its development by simulating human reasoning,[5] extensive research on mathematical theorems and foundations has been carried out. Early AI systems were inefficient, requiring substantial maintenance and incurring high computational costs. However, advancements in computational devices, their increasing capabilities, and the availability of large datasets have enabled the use of machine learning (ML), which presently plays a pivotal role in decision-making across various industries.

Nowadays, AI analytics is crucial to constructing decision-making processes. AI algorithms are created to update information based on collected data and optimize accuracy and efficiency. Reinforcement learning (RL) and neural networks (NNs) have significantly advanced AI's capacity to process data and accurately predict outcomes on the basis of data.[6] For instance, RL enables accurate active decision-making through trials and errors in its reward feedback mechanisms (Fig. 1). NNs are used to process unstructured data such as images and natural language to enhance the performance of computer vision and natural language processing.

In a rapidly changing business environment, using appropriate AI analytics is key to increasing profit. For example, Siemens has deployed AI-driven predictive maintenance systems using sensors embedded in factories to collect data on performance metrics such as temperature, vibration, and energy consumption. They have been using AI and ML algorithms to analyze the sensor data for equipment maintenance and product quality assurance. They have solved unscheduled equipment downtime that leads to considerable losses due to reduced productivity, delayed production, and high repair costs.[7] By predicting potential failures in equipment and manufacturing processes, Siemens determines the optimal maintenance to prevent unexpected breakdowns. This has reduced equipment downtime by approximately 30%. Amazon has used a combination of sensor data and AI analytics to optimize pricing and customer engagement. User behavior is identified from customer interactions on the website, including browsing history, purchasing habits, and search queries. AI algorithms analyze the data collected to implement a

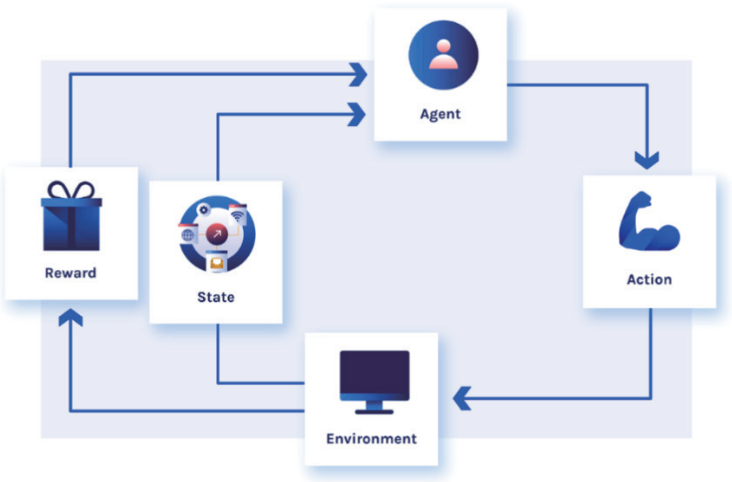

Fig. 1. (Color online) RL framework.

dynamic pricing strategy based on demand, competitor prices, and inventory levels. AI's capability to constantly adjust prices maximizes Amazon's revenue from each sale. AI-enhanced customer service and recommendation systems account for a significant portion of Amazon's total sales.(8)

AI analytics and sensor data help companies gain insight, make strategic decisions, allocate resources, and improve customer experiences effectively. For instance, companies can use ML algorithms to predict customer behavior and their purchases (Fig. 2).(9) Algorithms streamline routine tasks, allowing employees to focus on creative problem-solving and critical thinking, ultimately leading to improved decision-making. As industries are changing rapidly with the advent of technological advancements, effective decision-making aided by algorithms is increasingly important.

Referring to the previous achievements using AI analytics and sensor data to enhance a company's outcomes, we examined users' perception and experiences with AI analytics on the basis of sensor data for making decisions and enhancing a company's profit. To transform traditional business operational models to proactive and predictive ones, real-time data from a multitude of sensors and the analytical capabilities of AI are required. However, users' understanding of AI analytics and sensor data is essential for the successful development and deployment of these technologies. Such a human element influences adoption rates, trust level, and the adoption of related systems. A technology's success largely depends on its adoption by users, and understanding user needs and their perception is essential for further development of related technologies.(10,11)

Fig. 2. (Color online) Customer behavior prediction by using AI.

Therefore, the results of this study provide a reference for the evaluation of sensor and AI technologies based on users' perception in diverse industries. Technology developers can use the results to build a better technology that is user-centered and guided by how people perceive, trust, and interact with the technology.

2. Decision-making AI Algorithms

2.1 Algorithms

ML, as a subset of AI, is transforming the paradigm of decision-making algorithms by exploiting large amounts of data to make informed decisions. In ML, deep learning (DL) algorithms, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are widely used. CNNs are efficient algorithms for processing visual data, whereas RNNs are used mainly for image recognition because they can process sequential data efficiently (Fig. 3).[12] Such algorithms are used to process complex datasets to enhance decision-making ability.

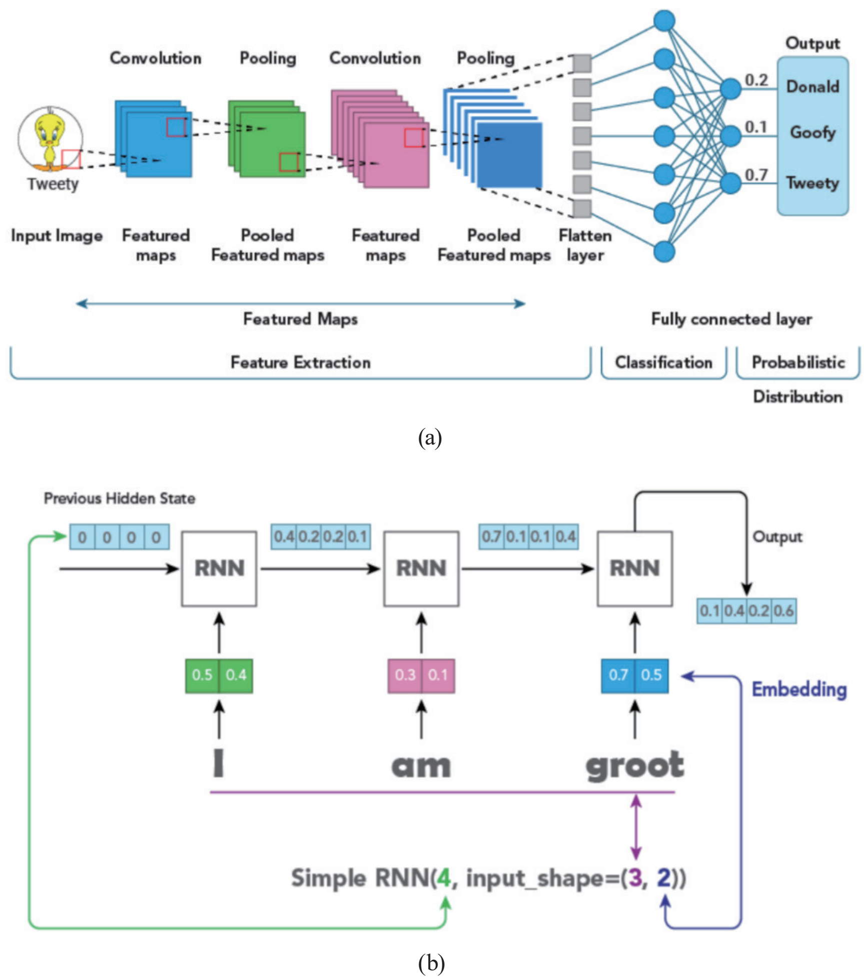

Fig. 3. (Color online) Structure of (a) CNN and (b) RNN.

To determine the algorithm efficiency in decision-making, Eq. (1) is mainly used.

$$E = \frac{1}{N}\sum_{i=1}^{N}\left(A_i - P_i\right)^2, \tag{1}$$

where E is the squared error, A_i is the actual outcome, P_i is the predicted outcome, and N is the number of observations.

An RNN comprises an input layer, a hidden layer, and an output layer. The RNN input is the last trial's reward in every step of its process. The output is a probability distribution of the last stage's reward. The hidden layer comprises a single-layer-gated recurrent unit (GRU) with five hidden layers, three of which are calculated as follows.

$$X_t = \left[r_{t-1} - a_{t-1} - t_{t-1}\right] \tag{2}$$

$$r_t = \sigma\left(w_{rX_t} + U_r h_{t-1} + b_r\right) \tag{3}$$

$$z_t = \sigma\left(w_{zX_t} + U_z h_{t-1} + b_z\right) \tag{4}$$

Using these layers, decision-making can be automated to supplement human judgment (Fig. 4).[13] For example, different customer behavior is predicted on the basis of marketing strategy adjustments. AI analytics increase decision speed and accuracy and allow companies to make

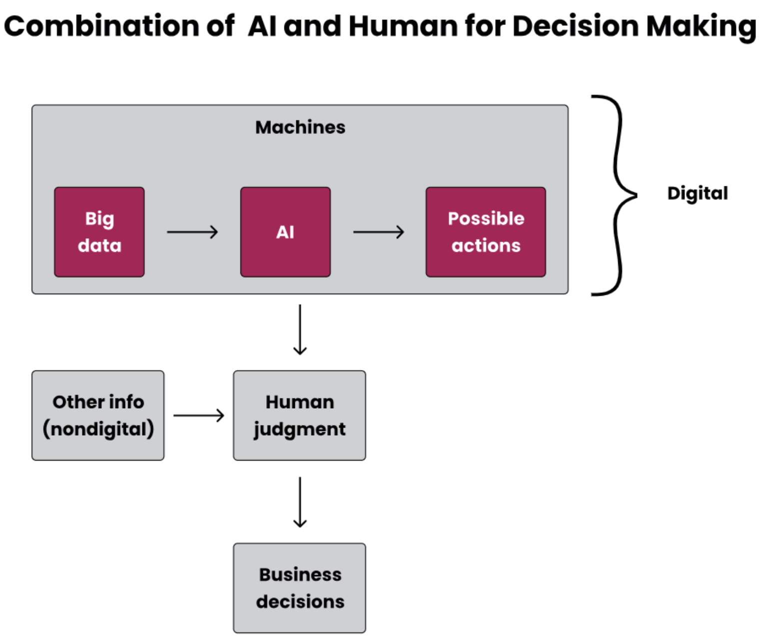

Fig. 4. (Color online) Combination of AI algorithms and human judgment in decision-making.

more strategic decisions. As companies increasingly rely on AI for decision-making, they must familiarize themselves with these technologies to enhance efficiency and fully leverage their benefits.

Moreover, the continuous advancement of AI algorithms has led to significant performance improvements in AI systems (Fig. 5). The AI algorithms' capability to train large and capable models using less computational resources allows companies to leverage AI algorithms for their decision-making applications more than before. Algorithmic efficiency leads to solving complex problems quickly. The results are used to enhance operational efficiency and innovation widely, such as autonomous vehicle development and smart city construction. For companies to remain competitive, utilizing AI algorithms in decision-making is becoming more critical.(14)

RL is enhanced by learning from previous trials and errors and rewards from previous steps. DeepMind's AlphaGo is a representative example of RL. Although RL has been deployed mainly to game development and playing, it is also used in robotics, financial technology, and healthcare analytics, for which an adaptive decision is critical. In decision-making algorithms, accurate prediction is necessary. An ensemble method such as random forest (RF) aggregates decision trees to improve accuracy and robustness in prediction. With noisy and complex data, RF is capable of accurate predictions. The ensemble method is an effective tool to improve the reliability of data-based and strategic decision-making.(15)

Big data analytics has played an essential role in developing AI analytics for decision-making. Data generated from various sources, such as social media, sensors, and other IoT devices, is used to make accurate decisions.(16) Since AI algorithms effectively process huge amounts of data rapidly and accurately, analytical tools capable of identifying patterns and trends in the data can be developed using the algorithms. Consequently, companies must increase investment in robust data and analytics infrastructure to fully leverage the potential of big data in decision-making processes.

When using AI analytics in decision-making, the role of human judgment can be overlooked. AI algorithms can analyze large datasets much faster than human decision-makers; however, their findings may be overly abstract, potentially missing underlying causes and insights that humans better recognize.(17,18) Therefore, companies need to balance the capabilities of AI analytics and humans in important decisions. Human and AI capabilities need to be integrated for better decision-making. Additionally, interdisciplinary collaboration is essential to integrate

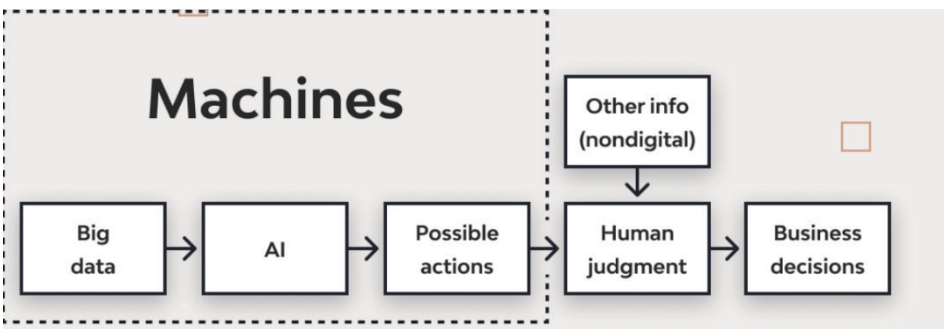

Fig. 5. (Color online) Decision-making model using AI algorithms.

diverse viewpoints to develop more robust AI algorithms for more sophisticated decision-making and potential risk mitigation. Through such collaboration, AI technologies can be used more responsibly and appropriately.

2.2 Example of algorithm application

The healthcare industry is a representative example of the application of AI algorithms and analytics that shows their power, as enormous volumes of data are accumulated. AI algorithms excel at processing data to uncover patterns that humans cannot identify and enable the prediction of disease progression from electronic health records (EHR) and the identification of anomalies in medical imaging using DL. In healthcare, decisions can be related to life or death situations. AI algorithms support the diagnosis of conditions, personalized treatment, and predictive models in AI-driven decision support systems, which leads to precision medicine.(19) In healthcare, predictive analytics is used to select appropriate treatments and recommendations for patients to avoid potential health risks.(20) In traditional methods, therapies are selected on the basis of the identified health issues. Predictive analytics benefits healthcare professionals and patients by identifying the risk of developing health issues and preventing the progression of diseases, which reduces healthcare costs. For chronic diseases such as diabetes and heart and respiratory diseases, predictive analytics enables proactive treatments and earlier intervention to prevent further progression of diseases.

In predictive analytics, ML algorithms are used to predict the progression of diseases on the basis of previous data collected from EHR, insurance claims, and wearable devices.(21) These algorithms learn patterns and correlations from the patient records and predict possible future medical incidents or new onset of a disease. A predictive model predicts the risk for a particular disease within the next 5 years on the basis of the medical history, lifestyle, and demographic factors of the patient. The model also recommends an appropriate lifestyle, medications, and regular checkups.

In predictive analytics, logistic regression is applied using the following model.

$$P\left(y=1\right)=\frac{1}{1+e^{-\left(\beta_0+\beta_1 x_1+\cdots+\beta_n x_n\right)}}, \tag{4}$$

where $\boldsymbol{\beta}$ is the coefficient learned from patient data.

Predictive analytics is also used to improve hospital operations and resource utilization. Hospitals can plan staffing, the number of beds, and equipment preparation by referring to forecasted demands. The model derived from predictive analytics identifies patients at high risk to treat them effectively. This holistic approach results in improved clinical outcomes, resource allocation, operational efficiency, and reduced healthcare costs.

In a hospital, an ML algorithm was used to predict congestive heart failure in a patient. The algorithm has been trained on historical big data of previous patients, including age, sex, ethnicity, medical history, lab results, medications, and others. The model found groups of patients highly likely to be readmitted within 30 days of discharge with high prediction accuracy.

The hospital identified the patients and made intensive interventions, including home visits, medication reconciliation, and patient education. Such interventions reduced readmission rates significantly, saved costs, and increased patient satisfaction. Such outcomes showed the benefits for healthcare and healthcare providers with proactive, personalized, and effective care services. The model enables a sustainable healthcare system with efficient resource utilization and increases patient satisfaction at a reduced cost. Such predictive analytics is expected to play a more significant role in the healthcare industry.

However, challenges must be addressed for the successful implementation of predictive analytics. First, large amounts of high-quality data are required. Appropriate data infrastructure and governance regulations are also necessary to deliver accurate, complete, and accessible outcomes. Second, appropriate AI analytics has to be utilized. Data scientists, clinicians, and other stakeholders must collaborate to effectively develop and implement predictive models.(22) Finally, predictive models need to be regularly assessed for their effectiveness and continuously updated to maintain their performance and potential.

3. Materials and Methods

To assess the effects of AI analytics and sensor data on the decision-making process, we conducted a survey of personnel who had been involved in AI-analytics-driven decision-making in various companies. We surveyed how AI-driven decision-making was utilized to solve complex problems and enhance operational outcomes in companies.

We conducted a questionnaire survey of those who had used AI analytics for decision-making at their companies. A structured questionnaire was developed, incorporating closed-ended questions to ensure clarity and consistency in responses.(23) The respondents were invited from the healthcare, financial, and autonomous system development departments of companies. The questionnaire survey was conducted on the Internet. To increase the response rate, reminders were sent repeatedly, and 91 respondents were obtained after omitting those with incomplete or inconsistent responses. The largest group of respondents (35) was working in the healthcare industry, whereas 30 were working in the financial industry, and 26 were involved in autonomous system development. The employment composition of the respondents reflected a well-defined and diverse distribution. The respondents were generally experienced, with the largest group (31 respondents) having more than five years of working experience. There was also a significant number with 3–4 years of experience (28), showing that the majority of the respondents were mid-to-senior level professionals. Forty-eight were male respondents and 37 were female (Table 1). Six respondents chose not to disclose their gender.

A questionnaire was created to determine how effectively they used algorithms and what outcomes they had attained. The respondents from the financial to autonomous system industries were invited to participate in this study. The data collected was analyzed by regression analysis, correlation analysis, and descriptive statistical analysis to examine the relationship between AI algorithm usage and decision-making effectiveness. Statistical analyses were carried out with Statistical Package for the Social Sciences.

Table 1
Industries, working experience, and gender distribution of respondents in questionnaire survey.

Attribute	Category	Frequency (n = 91)	Ratio (%)
Industries	Healthcare	35	38.50
	Financial	30	33.00
	Autonomous system development	26	28.50
Experience	Below 1 year	10	11.00
	1–2 years	22	24.20
	3–4 years	28	30.80
	5+ years	31	34.00
Gender	Male	48	52.70
	Female	37	40.70
	Prefer not to disclose	6	6.60

We obtained the descriptive statistics of the survey results and conducted regression and correlation analyses. Descriptive statistics included the means, medians, and standard deviations (SD) of scores, and the frequencies of the variables were included. Descriptive statistics led to the understanding of the demographics and experience with AI analytics of the respondents. Through regression analysis, we examined the relationship between independent and dependent variables to understand how different AI algorithms were used and affected decision-making in different industries. The results of the correlation analysis revealed the interdependencies among variables affecting decision effectiveness.

4. Results

4.1 Descriptive statistics

The perception of the effectiveness in decision-making, user experience with AI analytics, impact on decision-making effectiveness, and implementation challenges were analyzed using the scores of 91 respondents in the questionnaire survey (Table 2).

The perception of the effectiveness in decision-making scored 2.6945 on average with an SD of 1.08744. This indicated different opinions of the respondents on the effectiveness of using AI analytics. User experience with AI analytics scored 3.0923 on average with an SD of 0.56120. Most respondents had positive experiences with AI analytics. Impact on decision-making effectiveness scored 3.7253 with an SD of 0.50213, indicating that the respondents felt that AI analytics influenced their decision-making processes. Implementation challenges scored 3.7714 with an SD of 0.39052. The respondents perceived challenges in introducing AI algorithms into their companies.

These results suggest that AI analytics contributed to better decision-making and enabled better efficiency and accuracy, with advantages. However, challenges were pointed out concerning data quality, algorithm complexity, and the companies' lack of willingness to adopt the algorithms.

Table 2
Descriptive statistics of survey results.

	N	Minimum score	Maximum score	Mean score	*SD*
Perception of effectiveness in decision-making	91	1.00	5.00	2.6945	1.08744
User experience with AI algorithms	91	1.80	4.60	3.0923	0.56120
Impact on decision-making effectiveness	91	2.40	4.80	3.7253	0.50213
Implementation challenges	91	3.00	5.00	3.7714	0.39052
Valid *N* (listwise)	91				

4.2 Correlation analysis

The Pearson correlation coefficient between the perception of the effectiveness in decision-making and user experience with AI analytics was 0.457 at $p < 0.01$, showing a significant correlation between the perception and user experience with AI analytics. The correlation between the perception and impact on decision-making effectiveness was not significant (0.041, $p > 0.05$). This implied that the respondents found AI analytics effective but did not necessarily reflect their outcomes in decision-making. An insignificant correlation between user experience with AI analytics and the impact on decision-making effectiveness (−0.019, $p > 0.05$) also indicated that a favorable user experience with AI analytics did not significantly affect decision-making. However, a strong positive correlation (0.349, $p < 0.01$) was observed between implementation challenges and impact on decision-making effectiveness (Table 3). This suggests that challenges were recognized by the respondents in the implementation of the algorithms and affected decision-making processes to a certain extent. The results showed complicated relationships among the variables; however, AI analytics' effectiveness in decision-making, with perceived challenges surrounding them, can lead to better decision-making outcomes.

4.3 Regression analysis and analysis of variance (ANOVA)

Regression analysis was performed to determine how significantly the regression model predicted the dependent variables, the impact on decision-making effectiveness, as well as the dependent variables, the perception of effectiveness in decision-making, user experience with AI analytics, and implementation challenges. The R of the model was 0.351 with R^2 of 0.123 (Table 4). The three predictors (independent variables) accounted for about 12.3% of the variance of the impact on decision-making effectiveness.

The regression model showed a significant regression coefficient [$F(3, 87) = 4.063$, $p = 0.009$; Table 5], suggesting that at least one predictor significantly contributed to the variance in impact on decision-making effectiveness. Implementation challenges were a more significant predictor ($B = 0.448$, $p = 0.001$), indicating that overcoming the challenges in the implementation of AI analytics was essential to improve decision-making outcomes.

However, the perception of the effectiveness in decision-making ($B = 0.007$, $p = 0.890$) and user experience with AI analytics ($B = –0.029$, $p = 0.776$) did not significantly predict the impact on decision-making effectiveness (Table 6). This result showed that user experience with AI analytics and perception were essential to understanding AI algorithms and their applicability, but they were not correlated with decision-making effectiveness significantly.

Table 3
Correlation analysis results.

		Perception of effectiveness in decision-making	User experience with AI analytics	Implementation challenges	Impact on decision-making effectiveness
Perception of effectiveness in decision-making	Pearson correlation coefficient	1	0.457**	0.114	0.041
	2-tailed significance		0.000	0.281	0.701
	N	91	91	91	91
User experience with AI analytics	Pearson correlation coefficient	0.457**	1	0.016	−0.019
	2-tailed significance	0.000		0.879	0.855
	N	91	91	91	91
Implementation challenges	Pearson correlation coefficient	0.114	0.016	1	0.349**
	2-tailed significance	0.281	0.879		0.001
	N	91	91	91	91
Impact on decision-making effectiveness	Pearson correlation coefficient	0.041	−0.019	0.349**	1
	2-tailed significance	0.701	0.855	0.001	
	N	91	91	91	91

**Correlation is significant at the 0.01 level (2-tailed).

Table 4
Regression model summary.

Model	*R*	R^2	Adjusted R^2	Standard error of estimate
1	0.351[a]	0.123	0.093	0.47831

[a]Predictors: (Constant), implementation challenges, user experience with AI analytics, and perception of the effectiveness in decision-making
Note: Only 1 variable was needed, hence we used [a]

Table 5
Coefficients of regression model.

Model		Nonstandardized coefficient		Standardized coefficient	*B*	Significance
		B	Standard error	*B*		
1	(Constant)	2.107	0.562		3.747	0.000
	Perception of effectiveness in decision-making	0.007	0.052	0.016	0.138	0.890
	User experience with AI analytics	−0.029	0.101	−0.032	−0.285	0.776
	Implementation challenges	0.448	0.130	0.348	3.441	0.001

[a]Dependent variable: Impact on decision-making effectiveness
Note: [a] reprensents dependent variable

Table 6
ANOVA results.

Model		Sum of squares	Degree of freedom	Mean squared	*F*	Significance
1	Regression	2.788	3	0.929	4.063	0.009[b]
	Residual	19.904	87	0.229		
	Total	22.692	90			

[a]Dependent variable: Impact on decision-making effectiveness
[b]Predictors: (Constant), implementation challenges, user experience with AI analytics, and perception of effectiveness in decision-making
Note: Superscript [a] represents dependent/outcome variable; superscript [b] represents independent/predictor variables.

5. Discussion

In general, the respondents perceived the usefulness and recognized positive experiences in human use of AI analytics in decision-making, but simultaneously noted their implementation challenges. User experience with AI analytics and other variables were correlated to making better decisions. Using AI analytics in decision-making might be hindered by challenges such as data quality and resistance to its adoption. This highlights the need to comprehend user opinions and difficulties in implementing AI-driven solutions in the company's decision-making processes.

5.1 Perception of effectiveness in decision-making

The respondents did not perceive AI analytics' effectiveness in decision-making significantly. Previous studies showed that the potential of AI analytics did not necessarily imply their reliability and practicability. Owing to the complexity of the algorithms, it is not easy to understand and utilize AI analytics effectively.(24) Since companies are increasingly embracing AI analytics, education and training on utilizing AI analytics in decision-making must be conducted. The results of this study emphasize the importance of a favorable user experience with AI analytics to accept and effectively utilize AI algorithms.(25) The more beneficial and straightforward the algorithms are, the more favorably users use them for decision-making. Therefore, companies must enhance user experience with AI analytics by providing training, support, and feedback on the results.

5.2 User experience with AI analytics

The respondents had positive experiences with AI analytics, indicating the ease and usefulness of the algorithms. This is consistent with a previous study result showing the necessity of user-centered design of AI analytics.(26) AI analytics should be developed to meet users' needs. Additionally, the algorithms' design, interface, and features must be developed to promote their interactions with users. Data quality, algorithmic bias, and lack of transparency in using the algorithms must also be addressed.(2) Companies must optimize the user experience with AI analytics and encourage the active participation of users from the algorithm development to implementation.

5.3 Impact on decision-making effectiveness

AI analytics enables effective decision-making, which is dependent on the company's acceptance and available data.(27) Previous research results showed that AI analytics helps companies make better and more efficient decisions. However, companies need to proactively overcome the challenges related to decision-making effectiveness when implementation challenges exist. To enhance the decision-making effectiveness with AI analytics, companies must identify potential obstacles, such as users' resistance to the technology, by offering enough training opportunities.

Human judgment must also be considered to enhance the algorithms' impact on decision-making effectiveness.[28] AI analytics makes useful data-driven recommendations for decision-making, but human judgment helps make better decisions, as humans can consider underlying causes and insights. Human expertise and algorithmic capabilities must be harmonized for improved decision-making. To achieve shared goals and values, companies need to collaborate with data scientists and professionals with diverse expertise.

5.4 Implementation challenges

In AI analytics, data privacy and ethical considerations must be considered as the algorithms learn from previous data.[29] Companies need to have robust governance frameworks, policies regarding data usage, and training programs to utilize AI analytics effectively. Decision-making processes involving AI analytics must prioritize transparency to foster trust among stakeholders. The public acceptance of AI-driven decisions must be fair and accountable.[25] Companies must explain the reasoning behind the algorithms, the data used, and how decisions are made by the algorithms for the openness of the decision-making process. Potential bias or discrimination also must be minimized to build stakeholders' trust in AI-algorithm-driven decisions. Different AI algorithms have different advantages and challenges, as presented in Table 7.

First, companies must ensure data quality and availability in implementing AI analytics in decision-making. Most companies have incomplete, inconsistent, or out-of-date data, which undermines the effectiveness of AI analytics. Robust data governance must be formulated to guarantee data quality and availability. Existing datasets must also be audited and updated regularly.

Companies also need to mitigate the reluctance of employees to adopt new technologies. Training programs must be offered to educate users on the benefits and functionalities of AI analytics. Continuous feedback collection is required to foster the acceptance of the technology and ensure a smooth transition to AI-algorithm-driven decision-making.

Table 7
Comparison of benefits and challenges of different AI algorithms.

Algorithm	Category	Features	Advantage	Challenge	Application
RNN	DL	Processes sequential data; maintains hidden states for temporal dependencies	Excels in NLP, time-series forecasting, and speech recognition	Suffers from vanishing/ exploding gradients	Machine translation, text generation
CNN	DL	Uses convolutional layers for spatial feature extraction	Superior for image/ video tasks; automatically detects hierarchical features	Computationally intensive	Image classification, object detection, medical imaging.
Decision tree	Traditional ML	Splits data into branches using feature thresholds and tree-like decision paths	Interpretable and easy to visualize; handles numerical/ categorical data	Prone to overfitting; unstable with small data changes	Customer segmentation, fraud detection, credit scoring
RL	ML	Learns via trial-and-error interactions with environments	Ideal for dynamic environments (e.g., robotics, gaming)	Requires extensive computational resources	Autonomous vehicles, game AI (e.g., AlphaGo), robotic control

Ethical considerations are important to minimize biases and ensure transparency. As AI analytics demand training datasets that might contain private data or biased data, it is vital to ensure transparency in algorithm decision-making to build stakeholder trust. Acceptable practices for data collection and usage must be formulated for ethical data usage in the decision-making process.

Understanding the differences among AI algorithms is crucial for companies to appropriately select and adopt algorithms for decision-making. Traditional algorithms are appropriate for straightforward decision-making, whereas generative algorithms, such as ML, offer large potential for processing complex data. In Fig. 6 and Table 8, differences between the generative and traditional AI algorithms are also presented.

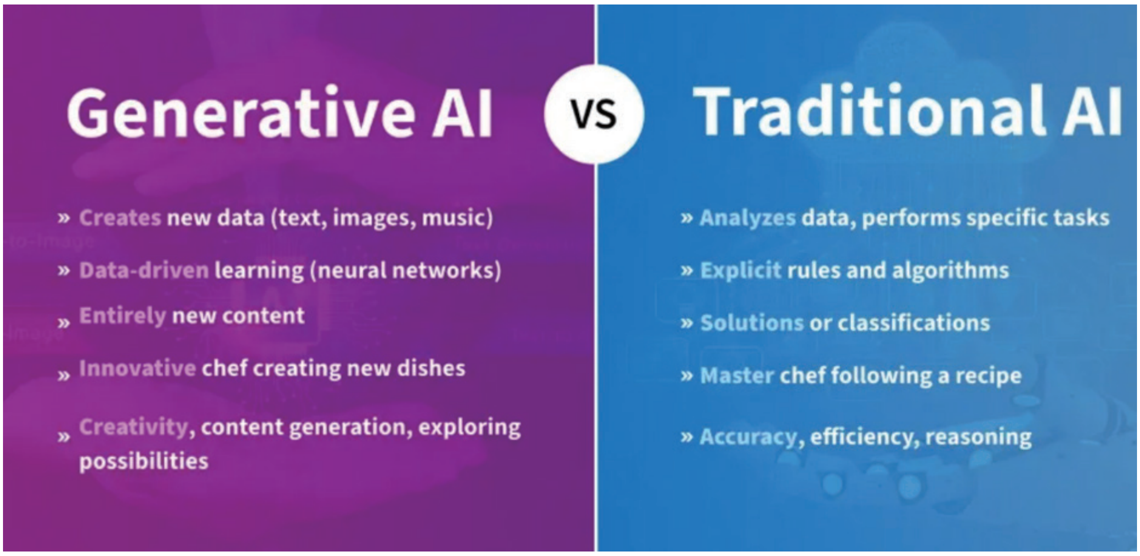

Fig. 6. (Color online) Generative and traditional AI algorithms.

Table 8
Comparison between traditional and generative algorithms.

Aspect	Traditional algorithm	Generative AI algorithm
Data dependency	Relies on structured and static data	Works with dynamic and unstructured datasets to identify patterns
Flexibility	Rigid; requires manual updates for changes in logic	Highly adaptable; can learn from new data and adjust accordingly
Problem complexity	Best suited for well-defined, deterministic problems	Excels in complex problems where patterns are not easily defined
Development process	Linear and predictable; focuses on implementing predefined logic	Iterative and experimental; involves training and refining models
Outcome predictability	Highly predictable outcomes based on known inputs and logic	Outcomes can be less interpretable, especially with complex models

6. Conclusion

We examined how to integrate AI analytics into decision-making and discussed the corresponding benefits and challenges. A structured questionnaire survey was conducted with 91 professionals on user experience with AI analytics, perception of the effectiveness in decision-making, impact on decision-making effectiveness, and implementation challenges. The potential of AI analytics was recognized by the respondents, but challenges in its implementation must be addressed.

We analyzed how perceptions of AI algorithms' effectiveness, user experience, impact on decision-making, and implementation challenges influenced decision-making effectiveness. Although AI analytics was found to be beneficial for improving decision-making efficiency and accuracy, challenges, including data quality, complexity, and organizational resistance, must be addressed. The perception of the effectiveness and user experience were significantly correlated, as were implementation challenges and impact on decision-making effectiveness. However, no significant correlation was observed between user experience with AI analytics and their impact on decision-making effectiveness. Implementation challenges were a significant predictor of the impact, accounting for 12.3% of the total variance. Implementation challenges were also critical to enhancing AI-driven decision-making. Perception and user experience with AI analytics were important, but did not significantly influence decision-making effectiveness. In using AI analytics for decision-making, data privacy and quality must be ensured to enhance decision-making effectiveness and transparency. Companies need to improve employees' experience with AI analytics and actively invest in data governance and training. Human expertise must be considered in AI-driven decision-making to ensure the efficient integration of AI analytics into the decision-making of companies in diverse industries.

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About the Authors

Jianlei Qian earned his B.S. degree in 2001 from Shandong University of Finance and Economics, China, followed by an M.S. degree in 2011 from Tongji University, China. Since 2001, he has been affiliated with Shandong University of Finance and Economics, where he currently holds the position of senior engineer. His research expertise includes networks, information engineering, and sensors. (qianjl@sdufe.edu.cn)

Kun Wang received her B.S. degree in 2004 and her M.S. degree in 2007, both from Shandong University of Finance and Economics, China. Since 2009, she has been serving as a lecturer at the same institution. Her research interests encompass data security, information engineering, and sensors. (wangkun@sdufe.edu.cn)

Zonglin Li received his B.S. degree in 2011 from Qingdao University, China, and his M.S. degree in 2014 from Harbin Engineering University, China. Since 2020, he has been an intermediate engineer at Shandong University of Finance and Economics. His research interests include sensor networks, natural language processing, and sentiment analysis. (lizonglin@sdufe.edu.cn)