International Journal of Information Technologies and Systems Approach
Volume 17 • Issue 1

Design and Implementation of an Intelligent Metro Project Investment Decision Support System

Qinjian Zhang, Shandong University, China & Guangzhou Metro Group Co., Ltd., China

Chuanchuan Zeng, Huazhong University of Science and Technology, China & China State Construction International Holdings Limited, China*

ABSTRACT

The construction of subway projects involves tight engineering cycles, multiple technical challenges, and complex coordination among various stakeholders. Due to the influence of uncertain factors during the construction process, the investment in subway project construction exhibits non-linear changes over time. Investment decision-making is the process through which the investment entity determines its investment activities. For typical investment entities, project investment decision-making primarily entails analyzing and evaluating proposed engineering projects based on investigation, analysis, and argumentation, ultimately deciding whether to invest. With the widespread application of information technology (IT) across various fields, decision support systems (DSS) have emerged to enhance the decision-making capabilities of enterprise management. This article designs an intelligent subway project investment DSS, leveraging data mining (DM) technology to integrate DSS with a data warehouse (DW).

KEYWORDS

Investment Decision Support, Subway Projects, System Design

In recent years, with the continuous expansion of urbanization, the number of permanent residents in cities has been on the rise, leading to increasing pressure on transportation networks. The original ground transportation vehicles can no longer meet the existing daily travel requirements, resulting in escalating traffic congestion (Iftekhar & Pannell, 2022). The emergence of urban rail transit has provided people with more convenient and timely modes of transportation while also alleviating the problem of road traffic congestion (Min & Rui, 2019). Urban rail transit boasts low environmental pollution, low energy consumption, and high transportation efficiency. These qualities effectively alleviate urban traffic congestion, making it a favored choice among the people (Martins et al., 2019). As the main artery of urban transportation, the investment and construction of subways are particularly crucial for alleviating urban traffic congestion (Huang et al., 2018). At present, subway construction in first-tier cities such as Beijing, Shanghai, and Guangzhou in China has achieved

DOI: 10.4018/IJITSA.342855 *Corresponding Author

significant results. Additionally, subway construction in cities such as Chengdu and Chongqing has also developed rapidly. China is gradually entering the peak period of subway construction (Kinjo et al., 2018). However, in addition to considering the issue of adding network sections and expanding the capacity of existing sections in general road traffic network design, investment in urban subway networks also needs to take into account the setting of subway lines and the temporal and spatial interrelationships of subway projects (Fowler et al., 2019).

Due to the fact that subway construction is mostly located in bustling and densely populated urban areas, the complexity and uncertainty of geological conditions, geological structures, and underground buildings increase the difficulty of construction. At the same time, it can also result in high construction costs and substantial investments in subway construction (Rossi et al., 2018). Making reasonable investment decisions under limited financial budget constraints to enhance the social welfare of urban systems and optimize the investment efficiency of limited financial budgets is an important research topic. Investment risk management is a crucial aspect of engineering project management. In addition to effectively increasing the risk awareness of the investment subject, it is necessary to prevent risks generated during the entire investment process of the project. This involves creating a safe environment throughout the entire project process to ensure the achievement of the goals of the engineering construction project. Engineering investment management personnel should initiate actions from the initial design, construction, and completion stages of the project, ensuring that investment management work runs through the entire process. Traditional management information systems are designed to address common structured problems, aiming to improve enterprise efficiency and strengthen enterprise management by processing large amounts of data into economically valuable information. As managers, it is essential to develop scientific management plans based on the characteristics of construction project investment, reduce unnecessary economic losses, and promote the achievement of the total investment goals of engineering projects (Zhao et al., 2023).

With the advancement of science and technology, individuals now seek not only to acquire usage information but also to fully leverage data information for supporting enterprise investment decisions. Enterprise investment decision-making involves the application of decision-making tools and control parameters across five management stages: investment planning, pre-project, investment planning, project implementation, and post-evaluation. The objective is to identify investment goals, determine investment scale, define investment direction, establish investment standards, and select investment projects. This process aims to prevent investment risks, allocate investment scale reasonably, enhance the economic benefits of investment projects, and elevate the level of investment efficiency in the planning and construction field. When constructing the DSS for subway project investment, multiple technologies and tools were comprehensively utilized. We use DM technology to extract useful information and patterns from historical data. At the same time, a data warehouse has been established as the core of data storage and management, ensuring the integration, stability, and temporal variability of data. During the implementation process, a database management system, professional DM tools, and data analysis software were used. With the support of this series of technologies and tools, we have successfully constructed a subway project investment DSS, providing accurate and real-time data support for decision-makers. The key innovations are as follows:

1. The intelligent DSS proposed in this article can leverage big data and AI technology to analyze massive amounts of data, offering decision-makers more precise and comprehensive information support.
2. Through visualization technology, the system presented in this article can portray complex data to decision-makers in an intuitive and easily understandable manner, significantly lowering the threshold for comprehending and utilizing data.
3. The system outlined in this article can collect, process, and update data in real time, ensuring that decision-makers can access the most recent information promptly, thereby enhancing the timeliness of decision-making.

4. This article begins by introducing the background and significance of the research. It then delves into the application of AI and big data technology in subway project investment. Subsequently, a comprehensive introduction to the investment DSS for intelligent subway projects is provided, followed by verifying its effectiveness and feasibility through experiments. In the conclusion section, the primary findings and contributions of this article are summarized, and future research directions and suggestions are pointed out.

RELATED WORK

The subway plays a pivotal role in the urban rail transit system by connecting various regions and transportation networks within a city. This integration enhances transportation efficiency, convenience, and environmental protection, ultimately fostering the growth of the urban economy. Amidst the ongoing advancement of information technology, artificial intelligence has experienced rapid progress. Both domestic and international research communities are actively exploring the application of novel technologies and methodologies to aid in subway investment decisions.

Patel et al. (2018) delineated urban sustainable development into three dimensions: social, environmental, and economic sustainability. Within this framework, they specifically analyzed the comparative advantages of rail transit vis-à-vis traditional public transportation. Meanwhile, Bouteraa (2021) utilized fuzzy mathematical theory to develop an engineering investment prediction model, demonstrating swifter predictions when compared to conventional investment estimation techniques.

Chabane et al. (2019) grounded their research on investment decision support for subway infrastructure in the grid theory of railway infrastructure. They segmented long steel rail equipment into uniform small sections, forming the basis for their two-part study. Jae Yeol et al. (2018) harnessed computers to evaluate historical data from completed projects, scrutinizing investment control strategies for upcoming projects. Liu et al. (2020) tackled the discrete optimization problem between project duration and cost in multimodal scenarios. Through computer-aided analysis of historical data, they arrived at practical solutions.

Wang et al. (2021) provided a comprehensive overview of the current status of subway development both domestically and internationally, outlining the fundamental principles of subway investment. Utilizing data from a specific subway, they conducted relevant research on denoising and mileage correction. Pascual-Paach et al. (2021) integrated the earned value method with BIM technology in construction cost control, yielding favorable application outcomes. Jemal et al. (2019) addressed challenges in the dynamic control of engineering progress and cost by combining BIM technology with earned value analysis. They employed WBS task decomposition to analyze deviations between construction process cost and time, optimizing deviation adjustment measures through comparative analysis (Huang et al., 2023; Feng & Chen, 2022).

Furthermore, Wang et al. (2021) devised a regression equation model that utilizes regression analysis methods to predict construction investment based on extensive completed project data. Oliveira et al. (2020) investigated the optimal investment decision problem within the context of subsidy support policy switching, formulating a decision model to assist investors in making informed choices when subsidy policies change. Lastly, Naranjo and Santos (2019) uncovered a fuzzy system for stock market investment decision-making rooted in fuzzy candle pattern recognition, shedding light on potential applications in the investment domain.

The currently employed traditional investment estimation methods have been empirically shown to exhibit low accuracy in predicting investment values, leading to significant deviations from the actual investment in engineering construction. The emergence of DSS marks another milestone in information system research. DSS seamlessly integrates knowledge from various disciplines, including computer science, behavior, and AI. Through interdisciplinary analysis, it examines the extent to which computers contribute to management decision-making. The intelligent subway project investment DSS proposed in this article has the potential to substantially enhance the efficiency and accuracy of subway project investment decisions. This system offers robust support for subway construction and management, signifying a significant advancement in the field.

THE APPLICATION OF AI AND BIG DATA TECHNOLOGY IN SUBWAY PROJECT INVESTMENT

Current Investment Status of Subway Projects

The investment characteristics of subway construction projects manifest primarily in the following aspects: Subway projects are public welfare endeavors, with their service functions oriented toward society and the primary benefits accruing to the public. Investment in subway projects is substantial, typically calculated in billions of yuan. The investment cycle of subway projects is relatively extended, often spanning 2–6 years. Subway projects are linear engineering endeavors, with sections situated in bustling urban areas and covering a wide range of locales. In the practical management of urban rail transit construction, obtaining timely monitoring information is often challenging due to factors such as terrain settlement, structural changes in the construction site, shifts in ground structure horizontal displacement, and internal forces acting on the support. Khazraeian and Hadi (2018) suggested a cost–benefit analysis approach utilizing Monte Carlo simulation, which was further integrated with the Analytic Hierarchy Process to aid in intelligent transportation system (ITS) investment decisions.

Additionally, Brcsk et al. (2020) crafted a guideline system rooted in survey data to comprehend and assess the public's preferences concerning energy supply. Furthermore, Boffardi et al. (2021) formulated a decision support system specifically designed to tackle waste management challenges in policymaking. Most subway transportation projects are situated in bustling urban areas characterized by dense populations, high traffic flow, and an intricate network of underground pipelines. Excavation or tunnel construction exerts a substantial impact on the surrounding environment, compounded by the complexity of various geological and mining landforms. The unique, intricate, and crucial nature of the construction process renders safety management more challenging compared to other projects. The inherent complexities make subway construction susceptible to risk accidents, including landslides or ground movements that can impact surrounding structures (Q. Ye et al., 2023).

The factors that contribute to engineering investment risks do not exist in isolation. Instead, the relationships between various factors are closely intertwined, and their combined influence can lead to investment risks in projects. Consequently, in project investment risk management, relying on a singular analysis method is inadequate, as it may be challenging to determine the probability and consequences of risk occurrence accurately. The precision of investment goals is paramount for successful construction investment control. However, determining investment goals is not a straightforward, deterministic problem. Investment goals undergo nonlinear stochastic changes over time, influenced by various factors. In real investment risk management, there is a tendency to analyze only quantifiable factors during risk analysis, overlooking the impact of non-quantifiable factors on investment risk. This approach results in a one-sided perspective on risk investment management and an inability to analyze and manage project risks scientifically.

AI and Big Data Technology

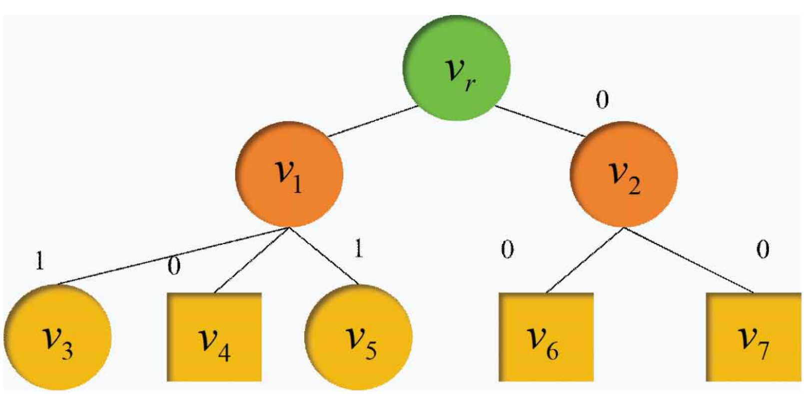
In the era of information and big data, the historical data of completed subway station projects can play a crucial role as a significant reference for predicting and controlling subway investments. By gathering information and data through various channels and sources, it establishes the groundwork for creating a spatiotemporal database of subway station construction investments. This database serves as a valuable resource for predicting and controlling future subway station construction investments. Laendner et al. (2019) delved into the progression from energy legislation to investment decision-making, taking into account various flexibility alternatives to mold the future electricity market. Meanwhile, Bracale et al. (2019) introduced a precise methodology for forecasting energy consumption and the performance of tunnel lighting systems, particularly in investment decision-making scenarios. Furthermore, Han and Kim (2019) examined a multi-cycle mixed integer linear programming (MILP) model tailored for a sophisticated renewable energy supply system on a national scale, thereby aiding decision-makers in investing in and designing renewable energy solutions.

When constructing a data warehouse for the subway project investment decision support system, we took a series of carefully designed steps to ensure the accuracy, real-time performance, and efficiency of the data. Firstly, we designed a data model based on decision requirements, including conceptual, logical, and physical models, to clarify the structure and relationships of the data. Next, we extracted data from multiple heterogeneous data sources, cleaned and transformed it, and loaded it into a data warehouse to ensure the accuracy and consistency of the data. At the same time, we implemented incremental and full load strategies to meet the needs of different data updates. In terms of data warehouse management, we focused on data maintenance, security, and performance optimization. We regularly updated data, implement backup and recovery strategies, and ensure the real-time reliability of data. In addition, we implemented access control and data encryption measures to ensure the security of data. In order to improve query performance, we optimized the indexes and query statements. Finally, we ensured the stable operation of the data warehouse through performance monitoring and troubleshooting mechanisms. Through these measures, our data warehouse provided powerful and reliable data support for the investment decision support system of subway projects.

Traditional databases are characterized by their speed and efficiency, enabling rapid data entry, modification, and querying. However, they come with significant limitations, unable to uncover the latent value within the data. Consequently, DM has garnered widespread attention (Ye & Zhao, 2023; S. Ye et al., 2023). The primary objective of data mining is to employ specific technical means to unearth concealed data. DM technology can be applied to enterprises to predict developmental trends and unveil unknown patterns. Utilizing DW as a carrier, DM technology facilitates further data processing and development. DM can be categorized into six groups: inductive learning methods, biomimetic techniques, formula discovery, statistical analysis methods, fuzzy mathematics methods, and visualization techniques.

Currently, inductive learning methods are the focal point of research, divided into two categories: information theory methods (e.g., DT) and set theory methods (e.g., clustering). This article primarily focuses on the DT algorithm and clustering algorithm. This system uses data mining algorithms such as decision trees and neural networks to extract useful investment decision rules through analysis and learning of historical data. Figure 1 illustrates the basic structure of the DT, a supervised learning algorithm employing a top-down recursive approach. Its fundamental concept involves constructing a tree with the fastest entropy decrease based on information entropy. At the leaf node, the entropy value is reduced to 0.

Figure 1. DT Structure



DSS DESIGN FOR INVESTMENT IN INTELLIGENT SUBWAY PROJECTS

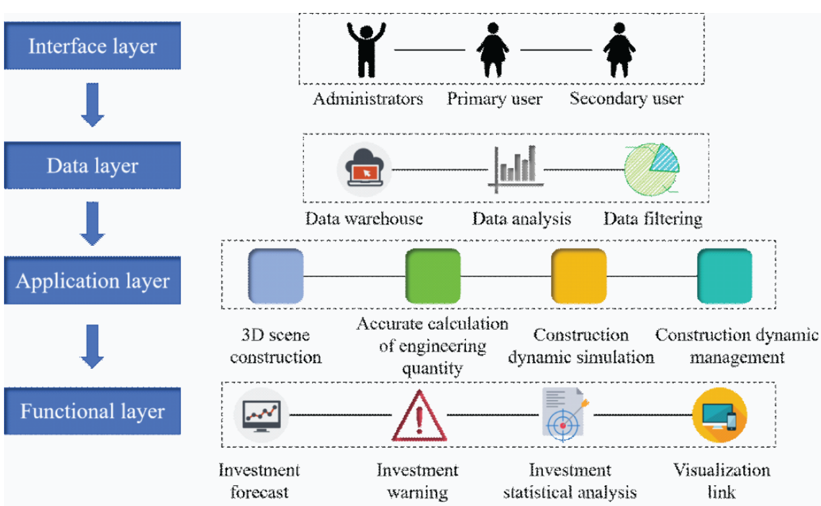
Systems Design

Computers play a vital role in storing and retaining vast amounts of knowledge, encompassing various rules, cases, and expert experiences. They facilitate the connection of knowledge with problems, link different pieces of knowledge, and aid in searching and reasoning to derive meaningful conclusions. In the operational context of a company, senior management often confronts a multitude of influencing factors, numbering in the dozens. Relying solely on the experience or intuition of managers for decision-making can pose significant risks to the company. Effective investment decisions are instrumental in enhancing the accuracy and efficiency of investments.

A rational and scientific investment plan serves as a crucial prerequisite for the stable construction and normal operation of engineering projects. Decision-making is a process of formulating a plan through preconceived conscious activities, involving a deep analysis of thinking during its execution. The essence of decision-making lies in research, analysis, comparison, and selection. When faced with multiple options, decision-makers must employ rigorous thinking to conduct a comparative analysis and make the most appropriate selection. The factors influencing investment in subway station construction are inherently complex. Analyzing the primary influencing factors and clarifying engineering characteristic indicators form the foundational work for accurately predicting engineering investment. This, in turn, enables dynamic intelligent visual control based on a substantial amount of historical data.

This article proposes the design of an intelligent subway project investment DSS, illustrated in Figure 2. The system administrators have the authority to manage the system, primarily tasked with overseeing system management functions. First-level users possess permissions that include acquiring the latest dataset, accessing the most recent analysis and results, and viewing various system-generated outputs and predictive charts. Secondary users are short-term valid accounts, temporarily added by administrators based on the internal electronic flow approval results of the company. These users can only access pre-authorized system datasets, analysis results, and charts, with their primary purpose being to share data with trusted external personnel. The data processing layer primarily comprises carriers used to persist various types of data. The business application layer encapsulates the core business logic of the comprehensive business system, built upon basic business components to achieve the core business process of security comprehensive monitoring and management. To streamline the

Figure 2. DSS for Investment in Intelligent Subway Projects



use of application systems and adopt a unified security control strategy, a unified single-point login is provided for users within the group's comprehensive security monitoring system.

The subway project investment decision support system consists of multiple core modules, each of which undertakes specific functions and implementation methods. The data preprocessing module is responsible for collecting, cleaning, and converting data related to subway project investment, ensuring the accuracy and consistency of the data. The data mining module utilizes advanced data mining algorithms to construct predictive models and evaluates and optimizes the models to discover potential value and patterns in the data. The decision support module presents the mining results to users in the form of charts and reports and provides targeted decision recommendations and risk assessments to help users make wise investment decisions. Finally, the system management module is responsible for tasks such as user management, data management, and system settings to ensure the normal operation of the system and the security and reliability of data. Through the collaborative work of these modules, the subway project investment decision support system can provide comprehensive investment decision support to improve decision-making efficiency and accuracy.

Algorithm Principle

Given the potential presence of more than two decision objectives in this DSS and considering that the input dataset may not strictly adhere to a specific distribution and that different indicator systems correspond to various data types, encompassing both continuous and discrete variables, it is deemed more appropriate to employ the C4.5 algorithm in the DT framework. At each node, the C4.5 algorithm calculates the information gain value of the node, traverse DT, identifies the node with the highest information gain rate, and establishes a node branch based on the test output of that node. Traverse DT comes again, iterated sequentially, gradually establishing a complete DT. Mark the tuple data of the training set as D class labels, assuming that D class labels have M different values, which represent M different classes, and label them as $C_i\left(i = 1, 2, \cdots, m\right)$, in sequence. The set of tuples in the C_i class is represented by $C_{i,d}$. $\left|D\right|$ represents the number of data in a tuple. The expected information required in C_i is:

$$Info\left(D\right) = -\sum_{i=1}^{m} p_i \log_2\left(p_i\right) \tag{1}$$

where $Info\left(D\right)$ is the legitimate value of D. p_i represents the probability that the data belongs to each tuple, and the calculation method for p_i is:

$$\left|C_{i,D}\right| / \left|D\right| \tag{2}$$

The scoring formula is employed to accurately calculate and tally the scores corresponding to the evaluation object indicators. Subsequently, the AHP is utilized to precisely calculate the overall project investment benefit score and individual project investment benefit scores. These scores are then subjected to statistical analysis, and corresponding investment benefit evaluation models are constructed. The formula for this model is as follows:

$$Y = \sum_{j=1}^{n} Y_j W_j \tag{3}$$

where Y_j represents the score corresponding to the first or second level indicator and W_j represents the weights of these two indicators.

Engineering characteristic parameters are the primary factors influencing cost indicators, serving as the intrinsic causes for variations in these indicators. Commencing with the fundamental significance of the impact weight of characteristic parameters on cost indicators, consideration is given to employing sensitivity analysis for weight determination. Sensitivity analysis involves calculating the investment change magnitude in the standard estimate model based on a unit value change in parameters. The calculation formula is expressed in Equation 4. The standard estimate model simulates unit engineering estimates by incorporating design guidelines, commonly used construction methods, and established standards for configurations in various regions.

$$W_k = \frac{r\left(v_k\right)}{\sum_{k=1}^{p} r\left(v_k\right)} \tag{4}$$

The decomposition of subway investment benefit evaluation is conducted through fuzzy attribute feature analysis utilizing the correlation feature fusion analysis method. The measurement value for subway investment benefit evaluation is then determined as follows:

$$U_{i,j}(t) = \exp\left[-b\left[z_i(t) - z_j(t)\right]^2\right] \tag{5}$$

Cosine similarity is an analysis method for measuring similarity based on space vector models, featuring straightforward operations and a well-established theoretical foundation. It is not influenced by the dataset distribution, it has a clearly defined range of values, and it is capable of rapidly processing high-dimensional data. This method finds extensive applications in classification. The cosine similarity between individuals is determined by the cosine value of the angle between the inner product spaces of vectors. The cosine value between vectors m and n is calculated using the Euclidean dot product formula, as shown in Equation 6:

$$\cos\theta = \frac{mn}{\left|m\right|\left|n\right|} \tag{6}$$

where m, n represents two vectors, mn represents the dot product of m and n, and $\left|mn\right|$ represents the Euclidean norm or length of m and n, respectively.

Taking into account practical application scenarios and data distribution characteristics, this article opts for the *k*-means algorithm to conduct clustering analysis on subway construction data. In the actual DSS design, the *k*-means algorithm is utilized to cluster construction costs and derive decision objectives in the construction cost prediction module. The *k*-means algorithm primarily assigns each point in the dataset to a cluster by evaluating the distance between attribute features influencing construction costs. The guiding principle for allocation is the proximity principle, indicating that a data point is assigned to a cluster if its Euclidean distance from the center point is small.

$$d = \sqrt{\sum_{i=1}^{n}\left(x_i^c - x_i^k\right)} \tag{7}$$

where n represents the number of data feature values.

Table 1. Test Environment

Project	Overview
CPU	Intel i5
Memory	6 GB
Operating system	Windows 7

Utilizing various types of functions, including quadratic, cubic, exponential, and power functions, accurately represents the relationship between the evaluation results of subway investment benefits and the investment amount. Subsequently, leveraging the fitting degree of the quadratic function, various indicator values are scientifically adjusted and controlled based on the subway construction situation. Building upon this, strict adherence to evaluation criteria and requirements is essential. The use of quadratic functions precisely captures the relationship between the current construction demand for the subway and the total investment amount, as expressed below:

$$y = ax^2 + bx + c \tag{8}$$

where x, y, a, b, c represents the indicator value, score, quadratic coefficient, linear coefficient, and random error term, respectively.

In the system implementation process, various technical means were adopted to optimize the system performance, including data caching and parallel processing. At the same time, we have also strengthened the security guarantee of the system, including measures such as data encryption and user permission management.

RESULTS AND DISCUSSION

To assess the performance of the system outlined in this article, empirical data analysis and simulation experiments were conducted. Utilizing SPSS 1.0 statistical analysis software and Matlab mathematical software, the key feature distribution dimension of subway investment fuzzy decision-making was 14, the correlation coefficient stood at 0.25, the DT layer was 12, and the interference intensity of the data was set at -10 dB. To ensure that the testing results objectively reflect the actual usage scenario, it is crucial to design a hardware testing platform closely resembling real-world conditions before commencing formal testing. Table 1 provides information on the system testing platform.

The safe and reliable operation of DSS in corporate subway investment has consistently been a focal point of concern for sociologists. The subsequent experimental tests use reliability as the testing indicator and present specific experimental comparison results in Figure 3. As depicted in Figure 3, the reliability of the designed system is significantly higher than that of traditional systems. The primary reason behind this improvement is that, in practical applications, analyzing and predicting changes in subway construction through fuzzy adjustment simulation feedback methods enables the system to make timely and accurate decision support. This, in turn, enhances the overall reliability of the system.

Optimization decisions for subway investment benefit evaluation were conducted, utilizing correlation testing and statistical analysis methods to perform regression analysis on subway investment benefit evaluation samples. The obtained evaluation results for asset return rate are illustrated in Figure 4. Upon analyzing Figure 4, it can be concluded that utilizing the system proposed in this article for subway benefit investment evaluation yields a substantial asset return rate of 10%. This indicates a high level of accuracy in the benefit evaluation process.

Figure 3. System Reliability Comparison

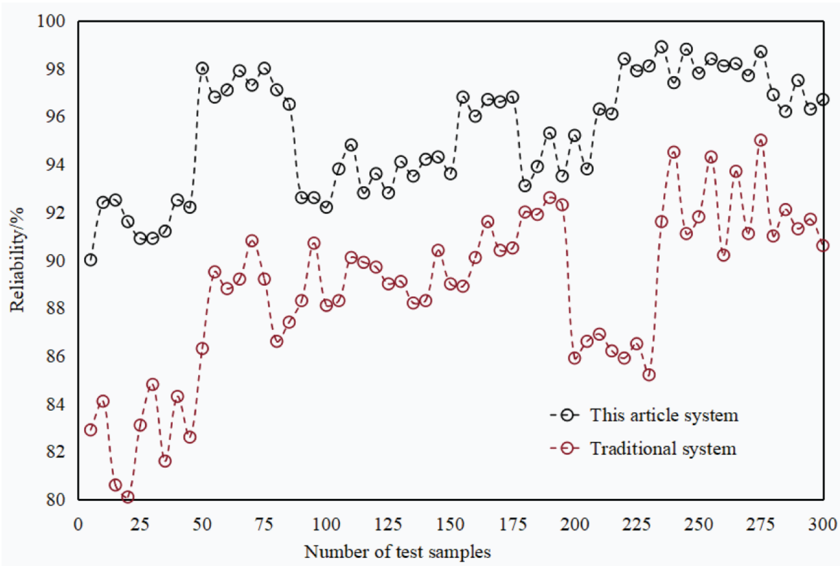
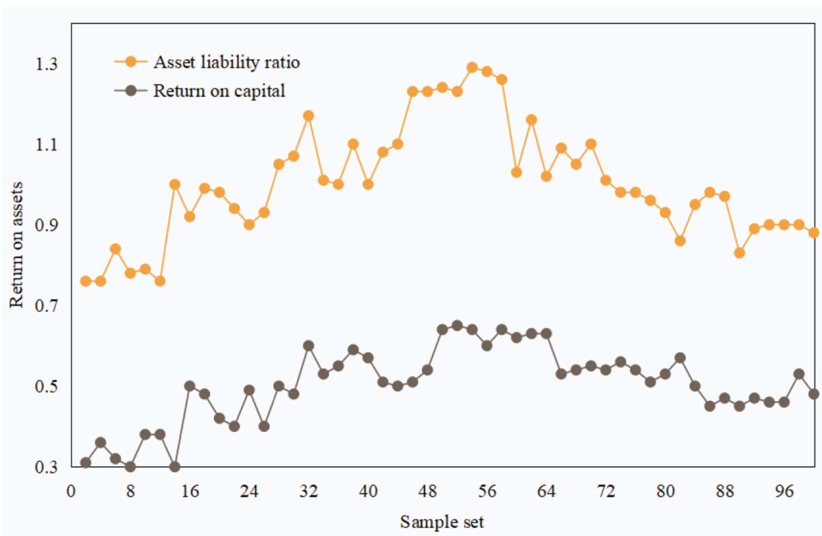
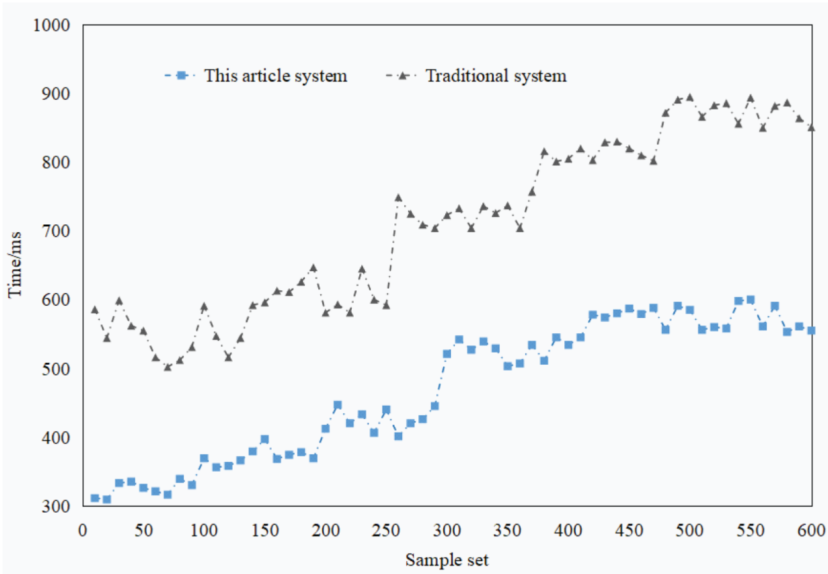


Figure 4. Asset Return Rate Evaluation Results



The system underwent pressure testing once again, specifically targeting performance by detecting the maximum pressure value. The method involved using relevant tools to monitor real-time CPU load, disk I/O quantity, memory usage, and bandwidth usage, collecting pertinent data. Figure 5 shows the comparison of system response time. Examining the response time of the contemporary system versus conventional systems across varying data volumes, the graph clearly demonstrates a direct correlation between data volume and response time. Notably, the system featured in this article consistently demonstrates a shorter response time than traditional systems, averaging a 35%

Figure 5. Comparison of System Response Time



improvement. This underscores the system's robust performance in handling substantial data loads, thereby guaranteeing dependable data processing.

The internal structure of each system varies significantly, potentially resulting in decision support errors when providing subway investment decision support for different enterprises. The following experiment employs the error rate of enterprise subway investment decision support as the evaluation indicator and presents detailed experimental comparison results in Figure 6. Observing Figure 6, it is evident that the designed system timely predicts the construction situation of the subway and

Figure 6. Comparison of Error Rates in Subway Investment Decision Support

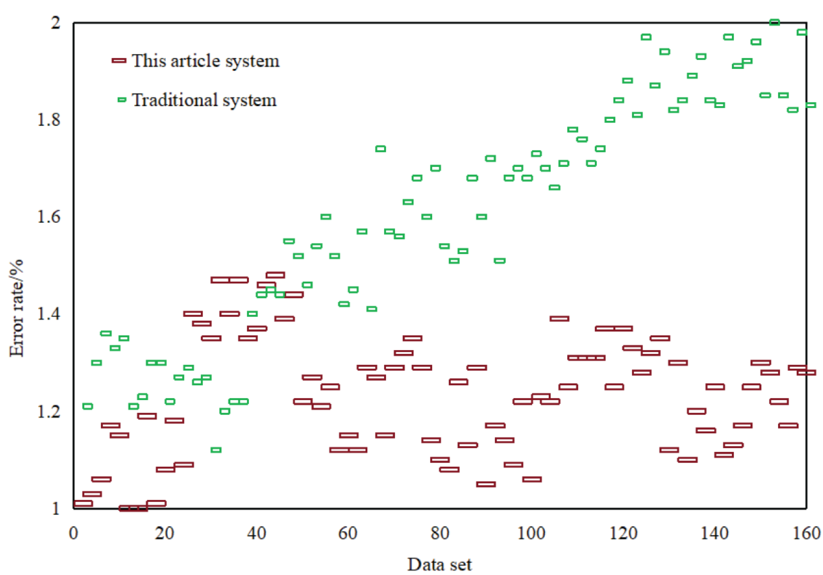


Table 2. Example Test Results

Project	Content	Method	Result
User login and new user creation	New system users can be added; the user successfully logs in	Based on test cases	Pass
Data acquisition function	The system information can be reflected accurately	Based on test cases	Pass
Decision support function	The predicted data and actual data can be displayed correctly	Based on test cases	Pass

adjusts the subway investment decision support plan in real-time based on the prediction results. This proactive approach effectively reduces the error rate of enterprise subway investment decision support. After employing the sample testing method to assess each module of the system, the test table presented in Table 2 was obtained.

CONCLUSION

In response to the emergence of "urban diseases" during the urbanization process, the government has implemented effective measures to encourage healthy and sustainable urban development. This involves increased infrastructure investment, promoting public transportation-oriented urban development models, and introducing suitable economic policies. Considering the current trajectory of development across various industries, the Internet has gradually become an integral part of various affairs, significantly contributing to its advancement. In addressing decision-making challenges, information systems present two paths: data and model decision-making. The approach presented here, built upon establishing a data warehouse, employs DM and data processing techniques to delve deeply into the data, providing effective information to management. The designed intelligent subway project investment DSS incorporates DM technology, combining DSS with databases to achieve the integration of model decision-making and data decision-making. This integration maximizes the advantages of both approaches, enhancing decision-making efficiency. The system provides comprehensive data services and decision support for managers. The experimental results demonstrate that the system designed in this article offers accurate and real-time information support for investment decision-making in subway projects. This improvement contributes to enhanced decision-making efficiency and accuracy.

Numerous factors influence investments in subway construction projects. In the analysis process, existing research findings, practical engineering cases, and the insights of engineering management personnel were considered. However, due to limitations in personal professional knowledge and research capabilities, the analysis of influencing factors may not be exhaustive. Considering the ongoing technological advancements, further enhancements to this system based on network, multimedia, and neural network technologies are envisioned to yield positive outcomes. Although this system has achieved good results in practical applications, there are still certain limitations, such as a high dependence on data quality. In the future, more optimization algorithms and models can be considered to further improve the decision-making efficiency and accuracy of the system.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

FUNDING STATEMENT

No funding was received for this work.

Received: February 3rd, 2024, Revision: February 20th, 2024, Accepted: March 6th, 2024

Correspondence should be addressed to Dr. Chuanchuan Zeng; t18127930208@163.com

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