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Application and Evaluation of Intelligent Management Accounting Platform Based on Association Rule Algorithm and PS-DR-DP Model

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Management accounting plays a key role in unit-level planning, decision-making, control and evaluation and is an important subfield of accounting. It is mainly intended to meet the internal management requirements of organizational units by utilizing relevant data and integrating financial and operational activities in a coherent manner. The management accounting platform is one of the centers of business management. Therefore, the stability and status of its platform requires extra attention. In this study, the researchers propose an intelligent management accounting platform assessment method based on big data association rules algorithm and a "pressure-support", "destructiveness-resilience", "degradation-promotion" model. The results revealed that the expert scores of the pressure and support indicator system ranged from 75 to 88, the destructive and resilient indicator system ranged from 69 to 93, and the degradation and enhancement indicator system ranged from 78 to 88. The credibility values of the three sub-indicator systems were 0.908, 0.989, and 0.955 respectively. Most of the carrying contribution values were below 0.9, and only the carrying state of support and degradation power in 2023 exceeded 1.0, at 1.6894 and 1.0832 respectively. Hence, the system was better equipped to withstand outside pressure as support, resilience, and deterioration all increased yearly along with the support capacity. The system damage or pressure resilience was improved, although the system may have some long-term degradation trends. The carrying state value also increased to 1.3956, and the mean value of carrying contribution increased significantly from 0.6025 to 0.9527 in 2023, indicating that the overall carrying capacity and contribution of the system is increasing year by year. It can be concluded that the proposed model can effectively assess the state of an intelligent management accounting platform. This provides a technical basis for promoting the management accounting platform to assess decision-making efficiency, resource allocation optimization, continuous improvement and strengthening of competitiveness.

Keywords: Association rule algorithm; management accounting; PS-DR-DP model; platform evaluation

1. INTRODUCTION

The rise in popularity of the Internet and the ongoing advancements in information technology have ushered in the big data era for management platform development. Big data technology is being used extensively in many different industries and is considered a significant advancement in the field of information technology [1]. In particular, its application is gradually becoming a trend in the field of

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management accounting. The Management Accounting Platform (MAP) system is one of the core elements of enterprise management. The information it contains is directly related to the enterprise's decision-making and future development path. The evaluation of its MAP is a critical activity for any company wishing to guarantee the efficient operation and ongoing development of tits management accounting system, which is crucial to boosting the organization's competitiveness and core values [2]. Therefore, it is imperative to evaluate the MAP system, evident by existing research and the many previous studies on the integration and association of the system and platform and other resource environments. To transition "from individual data research to data system research" and "from passive data validation to active discovery", a hypergraph-based Association Rules (AR) redundancy technique for data mining was proposed by Pane and Zhou algorithm for processing. The research method had better mining quality than the ARs mining using other two algorithms [3]. A paradigm for integrating and optimizing English teaching resources based on the ARs algorithm was proposed by Hou and Zhou. The test results indicated that their approach was more effective than both the hash technology-based Apriori algorithm and the original Apriori algorithm [4]. In order to forecast the outcomes of One Day International matches, Srivastava et al. proposed a hybrid machine learning clustering ARs model. This model uses deep neural networks, random forests, gradient enhancement, and other cutting-edge machine learning algorithms to implement a framework applicable to cricket matches. The results indicated that environmental conditions and internal quantitative factors were equally important in determining the outcome of the match [5]. Inspired by research in similar areas of frequent item sets simplifying inputs and parameter-free frequent item sets, Petr and Jan proposed a new algorithm. The algorithm found the best rule by counting the required rules for a given range in the output, proposing the SD4ft Miner algorithm for pairs of rules. The results of the study were verified by several applications on eight public datasets. The technique itself is efficient, taking up to 10 iterations, and may be applied to a larger class of procedures in any language [6].

The ongoing development of urban areas depends on whether enough water supply can be maintained. The coordinated growth of urban agglomerations greatly depends on accurate WRCC appraisal. Based on the theoretical framework of pressure support, damage recovery, and degradation promotion, Zhao et al. computed the WRCC index of the Beijing-Tianjin-Hebei metropolitan agglomeration. The findings showed that the study may serve as a resource for the creation of sustainable and scientific policies for the development of water resources and could help to five a comprehensive understanding of the present state of WRCC in Qinghua [7]. In China, soil pollution has emerged as a major environmental issue. It is crucial to conduct an impartial and thorough assessment of quality of the soil environment. A data fusion model and a driving force-pressure-state-impact-response (DPSIR) model were proposed by Zheng et al. for the assessment of soil environmental quality. The findings revealed that the use of fertilizers and pesticides, as well as the release of industrial pollutants, were the primary causes of soil pollution. The soil quality of industrial land was almost at the alert level, while the overall quality of the in the environment was moderate [8]. It is extremely important to continue to research ways by which China can maintain the sustainable use of natural resources, continual environmental improvement, and stable economic and social development. Based on the DPSIR framework, Sun et al. proposed a new indicator system for analyzing the relationship between complex socioeconomic-natural and resource-environmental systems [9]. A system for determining the health of mangrove ecosystems was established by Wang et al. using the pressure-state-response (PSR) model in conjunction with the analytical hierarchy process (AHP). The findings showed that the Gaoqiao mangrove region has outstanding ecological health [10].

In summary, for MAP assessment, researchers have covered and studied data identification and algorithm classification. However, there are still shortcomings in terms of data quality, assessment index system, technology application, cross-domain integration and dynamic adaptability. Therefore, a method based on an ARs algorithm and "pressure-support", "destructiveness-resilience", "degradation-promotion" (PS-DR-DP) model for intelligent management accounting platform (IMAP) evaluation is proposed. Then the IMAP system is integrated and analyzed using an ARs algorithm, and the evaluation system is constructed by combining the PS-DR-DP model.

This paper is organized as follows. The focus and innovation point of this research, the PS-DR-DP model and ARs algorithm, which form the basis of the IMAP evaluation approach, is covered in section 1. The experimental validation based on the method designed in the first section is described in second 2, which also examines the experimental data. Section 3 presents the experimental results, acknowledges the research limitations, and suggests directions for future research.

2. METHODS AND MATERIALS

First, the association of MAP data is analyzed, and a big data association rules (BDAR) algorithm is proposed. Secondly, an innovative IMAP evaluation method based on ARs algorithm and PS-DR-DP model is constructed. Combine AR algorithm and PS-DR-DP model to analyze the integration relationship of MAp and then evaluate the platform based on the PS-DR-DP model.

2.1 Algorithmic Study of Association Rules for Big Data

A stable and powerful MAP can provide decision-making support for an organization, help it to optimize resource allocation and improve its operational efficiency, thereby strengthening the competitiveness and core value of the business [11]. IMAP is a MAP based on business intelligence, which is the core of intelligent finance. By building IMAP enterprises can obtain multi-dimensional and three-dimensional data information that fits the needs of different users, and provide intelligent support for managers' decision-making process. In order to guarantee the platform's efficacy, support the enterprise's

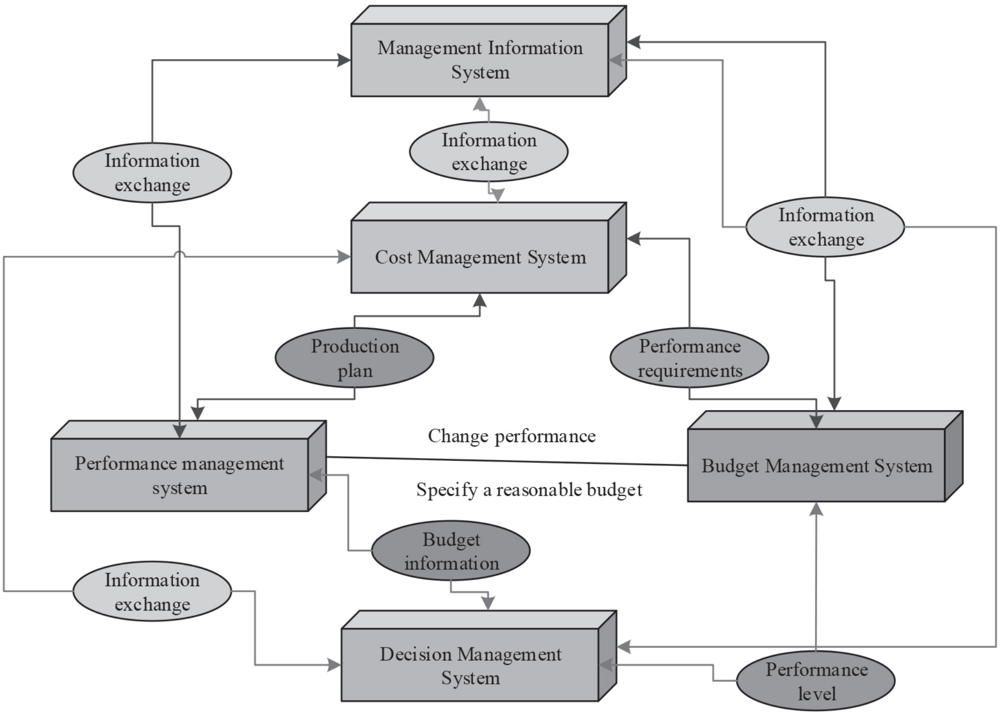


Figure 1 Integration relationship of IMAP.

strategic goals, strengthen the effectiveness of management, and encourage the enterprise's sustainable growth, it is critical to evaluate the MAP Businesses should be aware of how MAPs are rated and work to improve the platform's functionality and efficiency through ongoing optimization and development in order to better meet their internal management requirements [12]. The study uses BDARs algorithm in the evaluation application of MAp which focuses on the discovery of the association relationship in the data set, providing insights into the actual problem and decision support. The study performs big data association assessment of MAP The IMAP integration relationship is shown in Fig. 1.

As shown in Fig. 1, the platform includes information management, cost management, performance management, budget management and decision support systems. BDARs algorithm is a technique used in the field of data mining to discover association relationships between items in a data set. This algorithm is mainly used to analyze a large amount of data to find ARs between sets of items in the data. These rules can reveal patterns and relationships in the data which can help decision makers to make more informed decisions [13–14]. The fundamental functions of the AR algorithm are to find frequently occurring item sets and produce rules that meet predetermined support and confidence levels [15].

ARs reveal how different things are related to and dependent upon one another. One item can be predicted by the others if there is a definite connection relationship between two or more of them. The MAP assessment metrics set U is defined, and the set of metrics in it is selected as a transaction, as shown in Equation (1).

$$I = \{i_1, i_2, i_3, \ldots, i_m\} \tag{1}$$

In Equation (1), $i_1, i_2, i_3, \ldots, i_m$ represents the true subset of U, which is transformed into ARs for expression as $X \rightarrow Y \cdot X$ and Y represent the true subset, X, Y are the antecedent and the consequent, and there is no intersection between them. Support and confidence are important metrics for ARs algorithm. Support is defined as in Equation (2).

$$R = (X, Y).count/I.count \tag{2}$$

In Equation (2), R denotes the support degree (SD). $(X, Y).count$ denotes the items including both X and Y in the itemset. Confidence level is defined as in Equation (3).

$$Q = (X, Y).count/M.count \tag{3}$$

In Equation (3), Q denotes the confidence level. $X.count$ denotes the items that include only X in the I itemset. Equation (4) provides the calculation of the support and confidence derivation.

$$O(Y/X) = P(X, Y)/P(X) \tag{4}$$

In Equation (4), $O(Y/X)$ denotes the confidence level. A rule's low confidence level suggests that it will be more challenging to deduce Y from $X \cdot O(X, Y)$ denotes the SD. The support is calculated as in Equation (5).

$$O(X, Y) = O(Y/X) \times P(X) \tag{5}$$

No matter which ARs, the support is always higher than the confidence. The value of the threshold needs to be taken according to the support and confidence. Neither confidence nor support can be lower than the minimum threshold ($\min sup$, $\min conf$). First, a set $T = X \cup Y$ is set to satisfy as in Equation (6).

$$Q.count/I.count >= \min sup \tag{6}$$

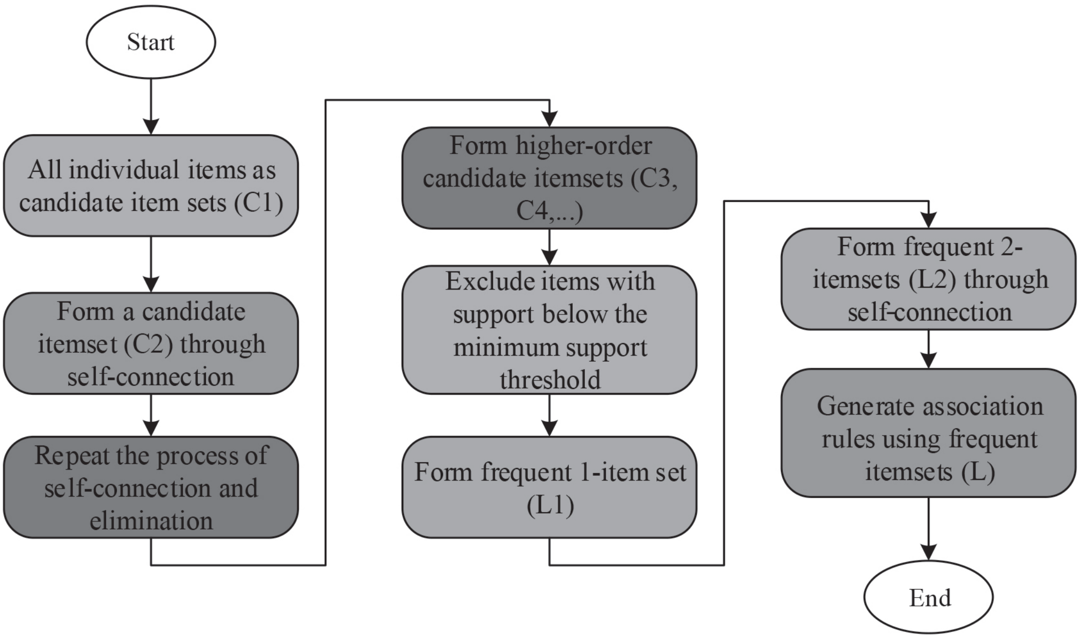


Figure 2 Association rule process.

In Equation (6), *Q.count* denotes the Q events contained in the I itemset, from which $X \rightarrow Y$ is subsequently found, which satisfies Equation (7) and $X = T - Y$.

$$(X, Y).count/X.count >= \min conf \tag{7}$$

Assume that there are r elements in U. A frequent itemset is a set similar to T. Denote the frequent itemset as $r-$ frequent itemset. According to the threshold value, the frequent itemset is interacted with the ARs and the result is derived for comprehensive assessment. Equation (8) illustrates the big data relevance expression. In data mining, data relevance is a significant factor in relevance assessment.

$$D = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\left(\sum_{i=1}^{n}(x_i - \overline{x})^2 \left(\sum_{i=1}^{n}(y_i - \overline{y})^2\right)\right)} \tag{8}$$

In Equation (8), D is the correlation coefficient between the two variables, x and y. $D = 1$ indicates a positive correlation between the variables x and y. $D = -1$ indicates a negative correlation between the variables x and y. $D = 0$ indicates that there is absolutely no correlation at all between the x and y variables. Typically, a $1 \leq D \leq 1$, signifying a linear relationship between the variables x and y [16]. The specific ARs are divided into two steps, as shown in Fig. 2.

As shown in Fig. 2, the process of generating frequent itemsets is divided into several steps. First all individual items are used as candidate itemsets (C1) and then candidate itemsets (C2) are formed by self-joining. Up until no new frequent item set is discovered, the self-connection and culling process is repeated to create higher order candidate item sets (C3, C4...) The items whose support falls below the minimal support threshold are removed to create the frequent 1-item set (L1). Next, by self-joining, frequent 2-item sets (L2) are created, and so on. The process of generating ARs utilizes frequent itemsets (L) to generate ARs. These rules satisfy the confidence level greater than the minimum confidence threshold (min *conf*) and automatically satisfy the minimum support (min *sup*) since the rules are generated based on frequent itemsets [17].

2.2 Evaluation Study of IMAP Combining PS-DR-DP Modeling

To determine the interactions between human activity and the environment, the PSR model uses a causal response framework. It is an assessment model commonly used in the subdiscipline of ecosystem health assessment, particularly for determining the quality of the environment. The PS-DR-DP model is a combination of the PSR and DPSIR models. There is a "PSR" relationship between human beings and the environment, as changes in natural and environmental conditions affect human socio-economic activities and well-being. This is evident in the ways that humans engage in different activities that pollute the environment while simultaneously obtaining from the natural environment the materials required for human sustenance and growth. Such activities can deplete natural resources and degrade the quality of the environment. Societies adapt to these shifts by creating sector-specific, economic, and environmental regulations as well as increasing awareness so as to alter human behavior [18–19]. On the other hand, the DPSIR approach is predicated on correlated indices and causal organizational data [20]. Consistent with the PSR framework, the DPSIR model is a framework based on causal organizational information and related indices. It aims to establish the causal chain of DPSIR, as shown in Fig. 3.

Fig. 3 presents the driving concept. Driving is a socio-cultural or socio-economic aspect that affects the amount of strain imposed on a watershed system. The primary driving force behind this pressure is its potential energy. To indicate the risks that social, economic, and human activity pose to

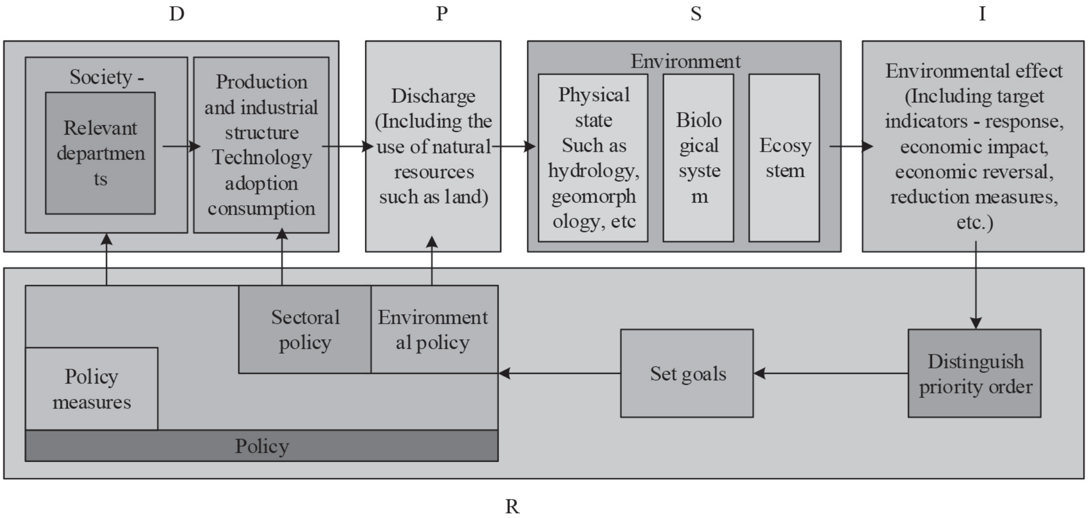


Figure 3 DPSIR model.

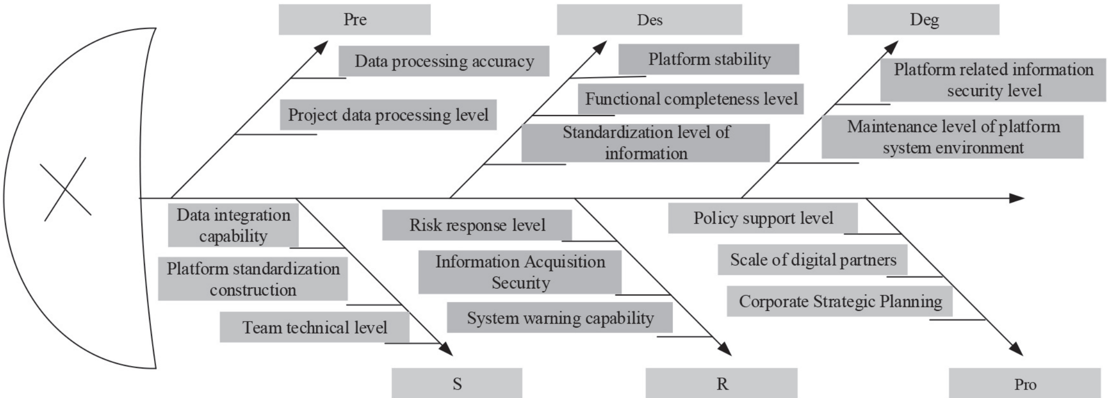


Figure 4 Fishbone analysis of indicator system.

the ecological security of the watershed, the DPSIR model can take into account social, economic, and environmental factors. Response indicators can also be used to illustrate how human activity affects society and how the environment responds to that [21–22]. The DPSIR model can make up for the fact that the evaluation grid in the PSR model cannot comprehensively consider the privacy of the surrounding resource environment. Therefore, the study combines the two models to propose the PS-DR-DP model research through the PS-DR-DP environmental evaluation model to build an IMAP assessment model for fishbone analysis as shown in Fig. 4.

Fig. 4 shows that the model is a positive hexagonal interaction force model. The study selected indicators for evaluation and analyzed the indicator confidence level α and set the confidence level control level. The confidence level $\geqq 0.9$ indicates very high confidence. A confidence level α between 0.7 and 0.9 indicates acceptable. Certain elements require revision, as indicated by a confidence level of α between 0.5 and 0.7. When the confidence level α is less than 0.5, it means that some things must be eliminated. The consistency evaluation of the indicator system of standardized items using confidence level is shown in Equation (9).

$$Q = (n/n-1)\left(1 - \sum E_i^2/E_t^2\right) \tag{9}$$

In Equation (9), denotes the overall variance of E_i^2 indicator variable (IV). n is the IVs. $\sum E_i^2$ denotes the sum of variance within each variable group. Q denotes the confidence level coefficient as shown in Equation (10).

$$\sum E_i^2 = \sum \left(H_i^m - H_m\right)^2 \tag{10}$$

In Equation (10), in the mth indication system, the variable's value is indicated by the letter H_i^m. The mean value of the variable in the mth indicator system is shown by the letter H_m. Subsequently, the expert scoring method is used to statistically analyze, process, and summarize the expert opinions, specifically by soliciting the opinions of relevant experts in an anonymous manner. It objectively synthesizes the experience and subjective judgments of most experts and helps to estimate numerous factors that are difficult to quantify using technical methods. The total number of indicator items in its guideline layer is shown in Equation (11).

$$P_i = \sum_{i=1}^{ki} P_{i_j} \tag{11}$$

In Equation (11), P_{i_j} denotes the jth indicator layer (IL) indicator in $P_i \cdot P_i$ denotes the criterion layer. k_i denotes the IL indicators in $P_i \cdot P_i$ denotes the i criterion layer indicator of

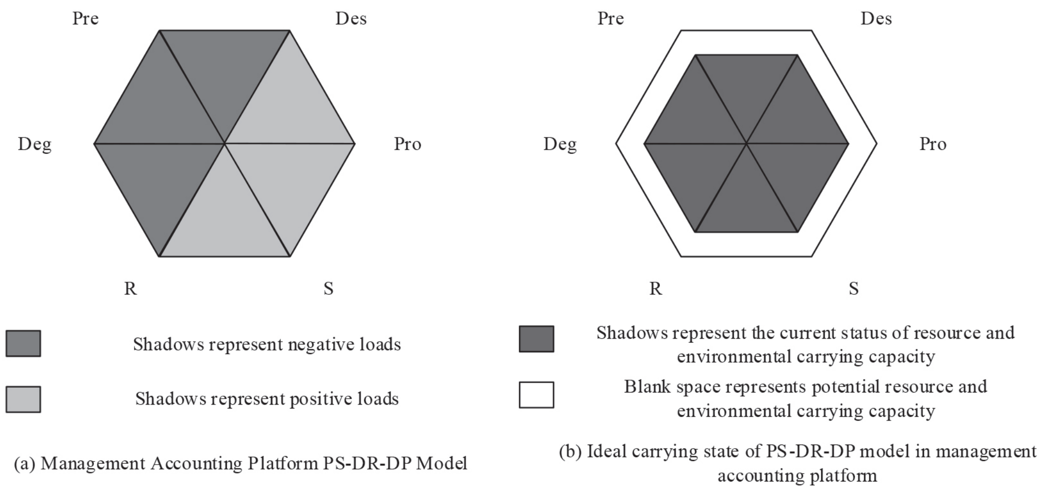


Figure 5 PS-DR-DP model and ideal carrying state of enterprise MAP.

the expert. The comprehensive evaluation of the target layer is shown in Equation (12).

$$A = \sum_{i=1}^{w} F_i P_j \tag{12}$$

In Equation (12), F_i denotes the weight of the criterion level indicator. P_i denotes the ith criterion level indicator of the expert. A_i denotes the final comprehensive expert qualification evaluation composite score. w denotes the total number. The study focuses on using expert scoring method, based on comprehensive index, weighting the reliability of expert scoring, and using it as the influence weight for evaluating expert scoring on various platforms in the later stage. The weighting coefficients are calculated with Equation (13).

$$\lambda_i = \frac{A_i}{\sum_{i=1}^{n} A_i} \tag{13}$$

In Equation (13), λ_i denotes the weight of the ith expert. $\sum_{i=1}^{n}$ denotes the sum of n expert qualification composite scores. A denotes the expert i composite score. The study introduces the platform carrying capacity contribution state value to analyze and evaluate the carrying state of the platform, as shown in Equation (14).

$$Z = \frac{\sum_{i<j}^{i,j} \cdot \left(H_i^m + 1\right)\left(H_j^m + 1\right)}{N(N-1)} \tag{14}$$

In Equation (14), H_i^m and H_i^m denote the values of the ith and jth indicators in the mth indicator system. N denotes each sub-item indicator. Z denotes the sub-item carrying capacity contribution value, as in Equation (15).

$$M = \frac{\sum_{i=1}^{i} T_i^p}{\sum_{j=1}^{j} T_J^n} \tag{15}$$

In Equation (15), T_J^n and T_i^p denote the jth negative contribution value and the ith positive contribution value, respectively. M denotes the carrying state. If this ratio is higher than 1, then the platform can handle a large amount of data and the carrying state of the platform is better. As this ratio increases, the platform can carry more information. However, if the ratio is lower than 1, this means that the platform is overloaded and needs to be repaired. The enterprise MAP PS-DR-DP model and the ideal carrying state are shown in Fig. 5.

Taking the MAP of an enterprise as an object, the evaluation index system is constructed using the ARs-based algorithm and PS-DR-DP model proposed in the study. The corresponding target layer and control layer indicators are established to evaluate the status of the platform and determine its effect. Table 1 displays the evaluation indicators.

3. RESULTS

An experiment was conducted to validate the proposed IMAP evaluation method based on the ARs algorithm and PS-DR-DP model. The corresponding design parameters and experimental data results are analyzed to verify the advantages and feasibility of the method.

3.1 Enterprise MAP Evaluation Index Setting and Application

The experiment takes the MAP of an enterprise as the object, and adopts the ARs-based algorithm and proposed PS-DR-DP model to construct the evaluation index system. The corresponding target layer and control layer indicators are established to assess the status of the platform and analyze the evaluation effect. The comprehensive evaluation indexes of expert qualifications usually include business level, comprehensive quality, personal information and other aspects, aiming at reflecting the professional ability and comprehensive quality of experts in a comprehensive and objective way. Table 2 shows the comprehensive evaluation indicators of experts' qualifications.

In addition, the carrying capacity of the platform resource environment is set. In level I, the platform carrying state is close to being stable, with a mean contribution value of $\leqq 0.35$. In level II, the platform carrying state is non-stable with a

Table 1 Evaluation indicators.

Target layer	Influencing factors	Index	Serial Number
Pre	Project data processing level	Platform user data	K11
		Supplier data	K12
	Accuracy level of data processing	Decision accuracy	K13
S	Data integration capability	Platform mathematical integration capability	K14
	Standardization construction	Platform standardization construction level	K15
	Team technology	Team technical capability level	K16
Des	Platform stability	Platform stability	K21
	Functional completeness level	The completeness of each functional module on the platform	K22
	Information quality	The credibility of information processing	K23
R	Risk response	Risk maintenance level	K24
	Information acquisition security	Obtain information security level	K25
	Platform warning capability	Risk warning level	K26
Deg	Security	Platform related information security level	K31
	System maintenance	Maintenance level of platform system environment	K32
Pro	Related policies	Policy support level	K33
	Digital partners	Scale of digital technology partners	K34
	Corporate strategic planning	Scale of enterprise digital strategy	K35

Table 2 Comprehensive evaluation indicators for expert qualifications.

Target indicator layer	Criteria level indicators	Weight/%	Indicator layer indicators
Comprehensive evaluation of expert qualifications	Educational background	20	Relevance of graduation major
			Years of professional education received
	Practice	30	Years of participation in practical platform work
			Number of related projects organized
	Theoretical capacity	30	The number of professional papers
			Level of publishing platforms for papers
	Industry sensitivity	20	Attention to industry policies
			Attention to industry development trends

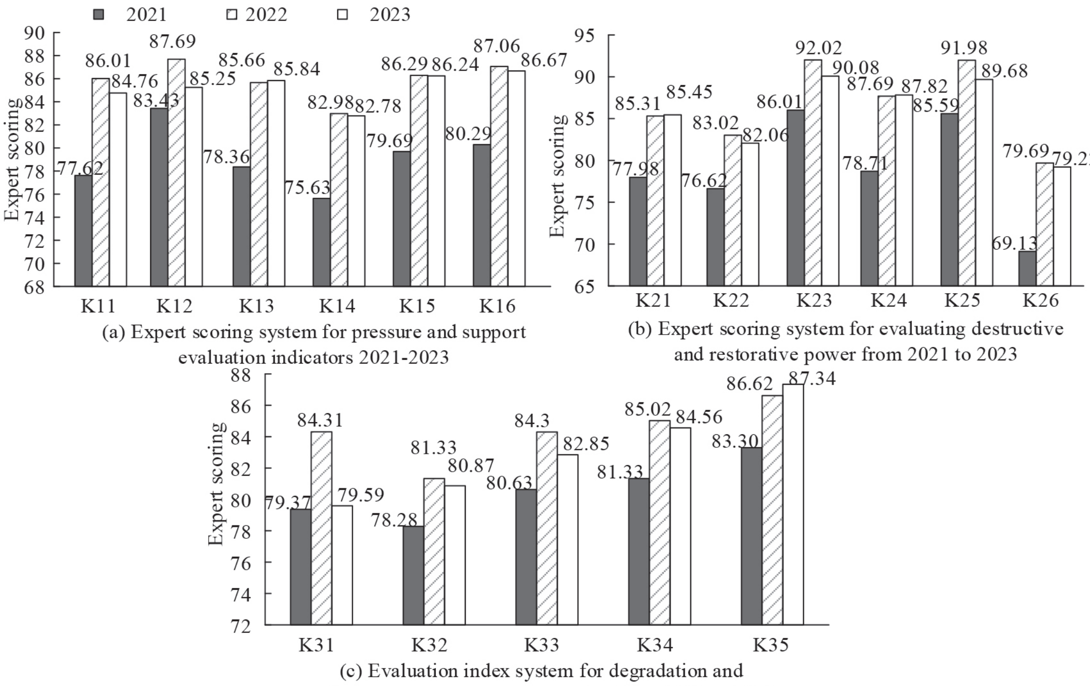
high growth rate, and a 0.35< mean contribution value of ≦0.70. In Level III, the platform carrying state is close to stable and therefore ideal, with a 0.70< mean contribution value of <0.85. In Level IV, the platform has full carrying capacity but tends to be non-stable, with a mean contribution value of ≧0.85.

3.2 Results of the Evaluation of the MAP of the Enterprise

Fig. 6 shows the expert scores of the evaluation indicator system for 2021–2023. In Fig. 6 (a)–(c), the expert scores of the pressure and support indicator system are between 75 and 88, the expert scores of the destructive and resilience indicator systems are between 69 and 93, and the expert scores of the degradation and enhancement indicator system are between 78 and 88. It is evident that the evaluation index method concentrates mostly on the 70–90 range.

To fully analyze the reliability of the numerical results, the experiment standardized the expert scores by min-max. Fig. 7 shows the standardized values and reliability analysis results of platform assessment index system of management accounting. In Fig. 7(a), all the values are within 1.0, all values are within 1.0, which means that the evaluation results of the sub indicator system have high stability and reliability, and can objectively reflect the platform's resource carrying capacity. In Fig. 7(b), the confidence level values of the three sub-indicator systems are 0.908, 0.989, and 0.955 respectively, suggesting that the proposed. model can effectively and objectively evaluate the resource carrying capacity of the platform.

Table 3 shows the analysis of IMAP state of the enterprise in 2021–2023. Only SUPPORT and degradation force have a CARRYING STATE of more than 1.0 in 2023, which are 1.6894 and 1.0832, respectively. Among them, support, resilience, and degradation force are increasing annually, as is the support capacity which is able to better cope with external pressure. The system's ability to recover from disruption or pressure is improving, although the system may degrade in the long term, requiring attention. Most of the carrying contribution values are below 0.9. The carrying state value also increases to 1.3956. The average value of the carrying contribution increases significantly from 0.6025 to 0.9527 in 2023, which indicates that the overall carrying capacity and contribution of the system is increasing every year.

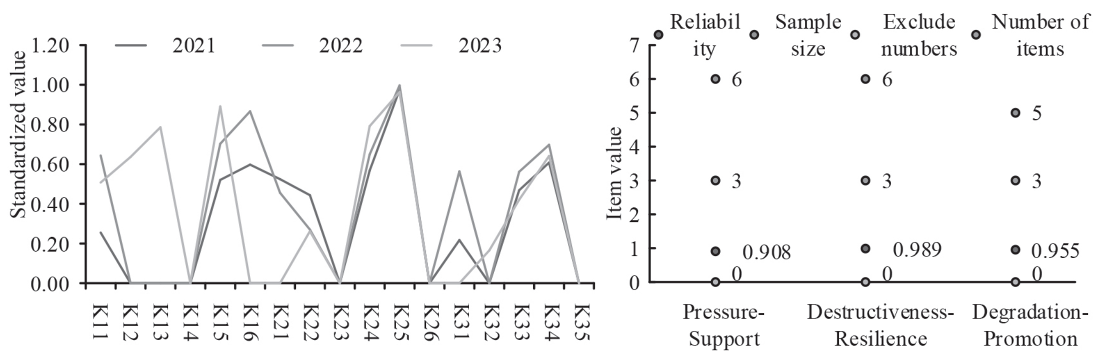


(a) Expert scoring system for pressure and support evaluation indicators 2021-2023

(b) Expert scoring system for evaluating destructive and restorative power from 2021 to 2023

(c) Evaluation index system for degradation and enhancement power, expert scoring from 2021 to 2023

Figure 6 Evaluation index system expert scoring from 2021 to 2023.



(a) Standardized values of evaluation index system for intelligent management accounting platform

(b) Analysis results of indicator credibility

Figure 7 Standardized values and reliability analysis results for the evaluation index system for the platform that manages company's accounts.

Table 3 Comparison of the carrying status of enterprise IMAPs from 2021 to 2023.

Carrying contribution value	2021	2022	2023
Pre	0.5651	0.8597	0.4946
S	0.4051	0.5298	1.6894
Des	0.7342	0.6167	0.8063
R	0.5161	0.5488	0.7926
Deg	0.6088	0.7818	1.0832
Pro	0.7877	0.8836	0.8496
Carrying status value	0.8956	0.8692	1.3956
Carrying average contribution	0.6025	0.7035	0.9527

Fig. 8 shows the resource and environmental carrying state of the MAP for the years 2021–2023. In Fig. 8(a), degradation and destructive forces are shown to be stronger, indicating that the tendency of the system's performance to gradually degrade or deteriorate over time and the ability of the system to be destroyed or damaged internally or externally by the system are stronger during this period. In Fig. 8(b), system pressure and destructive force are stronger, indicating that the external pressure or burden on the system or structure and the ability of destruction or damage caused to the system internally or externally are stronger in this period and need to be emphasized and paid attention to. In

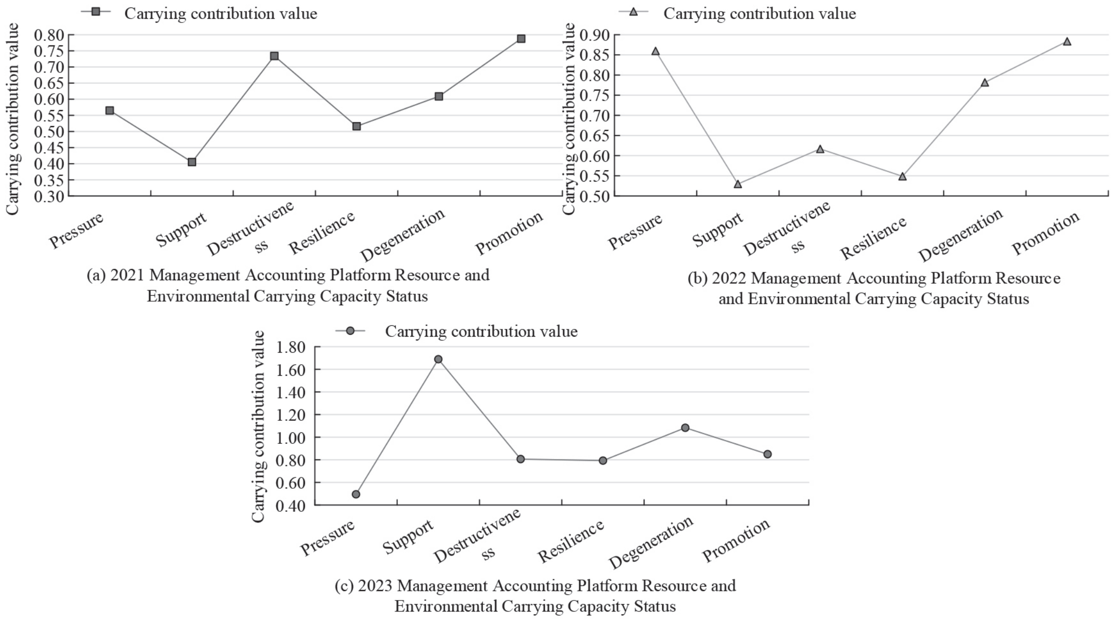


Figure 8 Status of resource and environmental carrying capacity of MAP from 2021 to 2023.

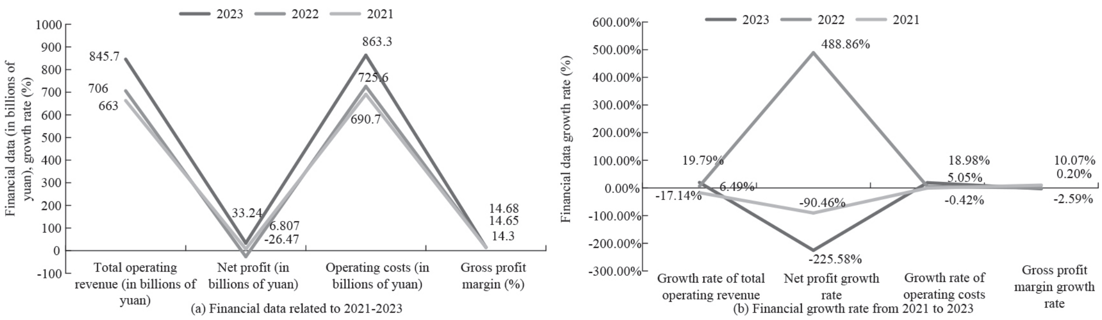


Figure 9 Financial data and growth rate for 2021–2023.

Fig. 8(c), support improves faster, from 0.4051 in 2021, to 1.6894, an improvement of 1.2843, indicating that the MAP is able to effectively resist and withstand the internal or external pressures on the system.

Fig. 9 shows the financial data and growth of the business from 2021–2023. In Fig. 9(a), the financial data of the business has decreased from 2021–2023 and has improved 6%, −489% and 5.04% year-on-year in 2022 for gross revenue, net profit, and cost of operations, respectively. In Fig. 9(b), the gross profit margin of the enterprise changes significantly in 2021, improving by 10.07%; the net profit increased the most in 2022, which is 488.86%. It can be concluded that the financial data are necessary for the development of an intelligent platform.

4. DISCUSSION AND CONCLUSION

To effectively evaluate IMAP the study proposes an IMAP evaluation method based on ARs algorithm and PS-DR-DP model. The ARs algorithm is combined to analyze the platform integration relationship, and then the PS-DR-DP model is used to construct the evaluation system. The outcomes revealed that most of the carrying contribution values of the platform were below 0.9, and only the carrying state of support and degradation force exceeded 1.0 in 2023, which were 1.6894 and 1.0832, respectively. Of these, the support, resilience, and degradation force were increasing annually, as was the support capacity. The system was better able to cope with the external pressure. The ability of the system to recover from damage or pressure was improving, although it may degrade in the long term and require attention. The value of the carrying state also improved to 1.3956, and the mean value of carrying contribution increased significantly from 0.6025 to 0.9527 in 2023, which displayed that the overall carrying capacity and contribution of the system was improving year by year. The degradation force and destructive force are stronger, the system pressure and destructive force performance was stronger, and the support enhancement was faster, increasing from 0.4051 in 2021 to 1.6894, an improvement of 1.2843. This indicated that the MAP was able to effectively resist and withstand both internal and external pressures. It can be concluded that the proposed method can effectively and accurately assess the resource carrying state of the platform. However, the platforms of many existing enterprises are in the early stage of intelligent transformation. Therefore, the MAP still has limitations, and the model needs to be improved and made compatible in subsequent research.

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