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Exploring the Role of Multiple Criteria Decision-Making in Enterprise Digital Transformation

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ABSTRACT

Global enterprises have accelerated their digital transformation due to the impact of the COVID-19 pandemic, especially those aspects related to the promotion of digital products, development of digital services, enhancement of data analytics, and wider artificial intelligence applications. Enterprises need to actively respond to these changes to maintain competitiveness. The multiple criteria decision-making (MCDM) process plays an important role in driving digital transformation for enterprises, which typically involves decision-making across many different dimensions and often requires consideration of multiple criteria. In this study, several experts involved in the relevant issues were interviewed. After brainstorming, they proposed several MCDM projects in response to digital transformation. The Bayesian best-worst method was applied to measure the relative importance and rank these projects. The analysis results suggest that "technology selection" and "evaluation of market competitiveness" are the two most important projects for promoting digital transformation for companies.

JEL Classification: M14, M15, O33

Keywords: multiple criteria decision-making, digital transformation, Bayesian best-worst method

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I. INTRODUCTION

The COVID-19 pandemic triggered a huge shift in the developed world towards digitalization. Digital transformation has become an important goal for every organization, department, and process within an enterprise. These developments have also led to significant changes in management culture, by the introduction of new technologies and ways of working, which may affect the key structures of a company's business operations (Priyono et al., 2020; Kraus et al., 2021; Kraus et al., 2022). The scope of digital transformation encompasses not just single enterprises, but also everything from the supply chain for the entire industry to the individual household's economy. To become a digital enterprise, for the organization operate interactively and create value, there must be support from top management and cooperation between employees (Manfreda et al., 2021; Tangi et al., 2021). In recent years, the research on digital transformation has shown the engagement of an increasing number of disciplines and perspectives from different fields with the issue of digital transformation. Although this has made the field more complex, it has also led to the development of more diverse ideas and insights (Hausberg et al., 2019; Hanelt et al., 2021).

There are various reasons for enterprises to pursue digital transformation, including improved productivity (Du and Jiang, 2022), enhancement of customer experience (Sahu et al., 2018), expanding the scope of the business (Ismail et al., 2017), optimizing competitiveness (Ferreira et al., 2020), and improving management efficiency (Llopis-Albert et al., 2021). Through the digitalization process, companies have to learn how to use new technologies and tools to improve productivity and reduce defect rates, facilitated by process automation, big data analytics, and artificial intelligence (Vaska et al., 2021). Regarding customer relationship management, digital transformation can help companies better understand customer needs, develop better products and services, and provide a better customer experience. In addition, digital transformation can help companies expand into new business areas and enter new markets, through online sales, e-commerce, and cross-border e-commerce. Companies need to adapt to the constantly changing market and digital technology trends to remain competitive. The importance of digital management has proven to be essential in the COVID-19 era (Vial, 2019; Chouaibi et al., 2022).

In digital transformation, the multiple criteria decision-making (MCDM) technique has played a crucial role. This is because digital transformation requires decision-making at multiple levels, within the enterprise itself and in the supply chain, which often involves multiple factors, such as cost, benefit, social impact, environmental impact, and risk. Through the MCDM techniques, enterprises can better manage and organize these complex decision-making processes and improve decision accuracy and efficiency. For example, MCDM can be used to evaluate and compare different digital transformation strategies. The enterprise can then choose the one that best suits their needs and goals (Maretto et al., 2022). Additionally, MCDM can help enterprises balance the needs and interests of different stakeholders during the digital transformation process. Through this approach, enterprises can better respond to market changes and competitive pressures, achieving long-term success and sustained development (Chen et al., 2022; Melo et al., 2023).

The purpose of this study is to explore MCDM for evaluating work projects for the implementation of digital transformation. The aim is to provide enterprises with an

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analytical tool for evaluation and selection problems (Beyaz and Yıldırım, 2020; Małkowska et al., 2021). The MCDM method has demonstrated excellent evaluation performance in complex environments. It does not require traditional statistics or fundamental assumptions, only a small sample of expert interview data. The goal of MCDM is to integrate objective survey data with subjective expert judgments to provide effective management information to support decision makers in formulating the best strategies (Fang et al., 2022; Lo, 2023). MCDM includes many effective techniques that can be used to handle various types of tasks such as: (i) handling the uncertainty of expert language variables (Chen, 2000); (ii) determining criteria/factor/item weights (Saaty, 1990); (iii) calculating a project's final performance (Opricovic and Tzeng, 2002); (iv) resource allocation and planning (Lo et al., 2021); (v) prediction and simulation (Shen et al., 2022), etc.

In this study, we invited senior experts from industry, government agencies, and academia who are engaged in digital transformation to form a decision-making team. The team identified seven projects that can assist in digital transformation, including technology selection, investment evaluation, risk management, cost-benefit analysis, evaluation of market competitiveness, measurement of customer experience and service quality, and recruitment of talent. The Bayesian best-worst method (Bayesian BWM) was used to measure the relative importance and priority ranking of the MCDM digital transformation projects. Bayesian BWM, as applied in this work, is a novel weighting method proposed by Mohammadi and Rezaei (2020), designed to improve the shortcomings of the analytic hierarchy process (AHP) and the original BWM. Specifically, AHP requires $n(n\text{-}1)/2$ pairwise comparisons of criteria, while BWM only requires $2n\text{-}3$ comparisons. Although BWM requires a greatly reduced number of pairwise comparisons, it cannot effectively aggregate expert opinions. Bayesian BWM uses the statistical probability distributions to obtain the most suitable criteria weight allocations from the expert group. This method can achieve a better expert consensus and improved reliability of weight allocation. The special characteristics and contributions of this study can be summarized as follows:

1. The MCDM method described in this study helps decision-makers better understand the work projects which can assist in promoting digital transformation.
2. This MCDM method identifies the priority of these work items for digital transformation.
3. This study also formulates some management implications as recommendations for promoting digital transformation.

II. LITERATURE REVIEW

This section briefly reviews the application examples of Bayesian BWM and then describes seven MCDM evaluation projects.

A. A Brief Introduction to Bayesian BWM

Bayesian BWM is a MCDM method that determines the optimal criteria weights and rankings by selecting the best and worst criteria and comparing them to other criteria. Currently, this method has been widely applied in various fields. For example, AK and

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Yucesan (2022) applied Bayesian BWM to evaluate occupational risks, resulting in a prioritized list of six criteria and their weights. The study showed that the risk of electrical work was the highest, and this finding could help practitioners and management to formulate improvement measures to enhance workplace safety and reduce the occurrence of work accidents. Hashemkhani Zolfani et al. (2022) employed Bayesian BWM to find the best country for lithium battery production based on seven evaluation criteria, concluding that Chile is the most suitable country to establish the lithium battery industry. This study can assist managers in formulating appropriate development strategies. Saner et al. (2022) used Bayesian BWM to evaluate the disaster prevention capability of hospitals, considering 34 criteria, and found that "personnel emergency response capability" is the most important factor. This study provides a better foundation for hospitals to enhance their emergency response capabilities. Yanilmaz et al. (2021) adopted Bayesian BWM to conduct a disaster analysis in Turkey, evaluating and ranking nine different disasters in the Tunceli region. The study results showed that "earthquake" ranked first. Debnath et al. (2023) introduced Bayesian BWM to identify key factors for promoting the lean production of the furniture manufacturing industry. The analysis result indicated that sustainable resource utilization, reduced delivery time, management support, and innovative technology are the four critical factors for implementing lean production in the furniture manufacturing industry. This finding will help management and related organizations to develop effective action plans.

B. Seven MCDM Evaluation Projects That Can Assist in Promoting Digital Transformation

This study established a decision-making team to discuss the MCDM evaluation projects for digital transformation of an enterprise. A total of 32 experts from industry, government agencies, and academia, with many years of experience in digital transformation and holding at least a master's degree, were invited to participate. Table 1 summarizes the background information of all the experts.

All members of the expert panel provided relevant data and information as an introduction to themselves, their area of expertise, experiences, perspectives, and opinions. The experts were divided into groups for in-depth discussions and exchanges, allowing a deeper understanding of each group's ideas and exploring the decision-making problems and challenges that enterprises face in digital transformation. Finally, recommendations from all 32 experts were summarized and seven potential major projects were proposed.

- Technology selection (D_1): This project refers to evaluating and selecting feasible technological solutions for digital transformation in order to determine the most suitable technology for the company's needs (Van de Kaa et al., 2014; Krishankumar et al., 2022).
- Investment evaluation (D_2): This project refers to evaluating the investments made by the company for digital transformation and determining their value and benefits (Tsai et al., 2009; Huang et al., 2020).
- Risk management (D_3): This project refers to evaluating and managing various risks associated with digital transformation to reduce the loss and impact caused by these risks (Lo and Liou, 2018; Gul and Ak, 2021).
- Cost-benefit analysis (D_4): This project refers to evaluating and analyzing the costs

and benefits of digital transformation and determining the investment value and benefits of digital transformation (Annema et al., 2015).

- Evaluation of market competitiveness (D_5): This project refers to evaluating and analyzing the market competition faced by the company using digital transformation to enhance the company's competitiveness (Wang and Tzeng, 2012).
- Measurement of customer experience and service quality (D_6): This project refers to evaluating and measuring the products and services provided by the company using digital transformation to enhance customer experience and service quality (Oladipupo et al., 2021).
- Recruitment of talent (D_7): This project refers to recruiting and selecting the talent needed by the company to ensure that it has sufficient manpower resources to support the implementation and execution of digital transformation (Sehatpour et al., 2022).

Table 1
Background Information of 32 Experts

Expert ID	Category	Department/job title	Years of experience	Educational background
Expert 1	Industry	Information technology manager	12	Master's
Expert 2	Industry	Project Manager	23	Master's
Expert 3	Industry	R & D manager	15	Master's
Expert 4	Industry	Project Manager	14	Ph.D.
Expert 5	Industry	General manager	30	Ph.D.
Expert 6	Industry	Industrial engineering manager	15	Master's
Expert 7	Industry	Industrial engineering manager	16	Master's
Expert 8	Industry	Information technology manager	20	Master's
Expert 9	Industry	Information technology manager	15	Ph.D.
Expert 10	Industry	R & D manager	10	Ph.D.
Expert 11	Industry	Project Manager	16	Master's
Expert 12	Industry	Information technology manager	20	Master's
Expert 13	Industry	General manager	25	Ph.D.
Expert 14	Industry	Information technology manager	20	Master's
Expert 15	Industry	Industrial engineering manager	15	Ph.D.
Expert 16	Government agency	Institute for Information Industry	12	Ph.D.
Expert 17	Government agency	Institute for Information Industry	10	Master's
Expert 18	Government agency	Association of Machinery Industry	13	Ph.D.
Expert 19	Government agency	Association of Machinery Industry	15	Master's
Expert 20	Government agency	Institute for Information Industry	13	Ph.D.
Expert 21	Government agency	Industrial Technology Research Institute	15	Master's
Expert 22	Government agency	Industrial Technology Research Institute	16	Masters'
Expert 23	Government agency	Industrial Technology Research Institute	20	Masters'
Expert 24	Academia	Department of information management	15	Ph.D.
Expert 25	Academia	Department of information management	20	Ph.D.
Expert 26	Academia	Department of information management	20	Ph.D.
Expert 27	Academia	Department of business administration	21	Ph.D.
Expert 28	Academia	Department of Business Administration	22	Ph.D.
Expert 29	Academia	Department of Business Administration	22	Ph.D.
Expert 30	Academia	Department of Business Administration	10	Ph.D.
Expert 31	Academia	Department of industrial engineering and management	15	Ph.D.
Expert 32	Academia	Department of industrial engineering and management	13	Ph.D.

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III. METHODOLOGY

This section provides an explanation of the Bayesian BWM employed and outlines the step-by-step calculation process. The original BWM offers an advantage over the AHP in terms of its consistency testing, and its execution steps are straightforward. The BWM selects the best and worst criteria, and then compares the remaining criteria with these two to form two groups of structured vectors. This structure allows decision-makers to obtain more dependable results. Moreover, the unique structure of the original BWM produces two vectors (A_B and A_W) composed solely of positive integers, which overcomes the disadvantages of AHP's fractional forms (e.g., 1/a) and the associated distance problem.

However, depending upon calculating the arithmetic mean to combine the opinions of multiple experts is not recommended in BWM because of variations between the information in the two vectors arising from the different opinions provided by each expert. Therefore, Mohammadi and Rezaei (2020) proposed the Bayesian BWM to overcome the above problem. Its principles and steps are explained in detail below.

A. Step 1. Identifying a Set of Projects

The expert team determines n projects for the evaluation system, which are labelled D_1 to D_n.

B. Step 2. Selecting the Best and Worst Projects

Experts select the most important and least important projects from D_1 to D_n.

C. Step 3. Generating the BO (Best-to-Others) Vector

The BO vector is constructed using the 9-point scale (shown in Table 2, where 1 indicates equal importance and 9 indicates absolute importance, with higher values indicating greater importance), by comparing each project to the most important project (Equation 1).

$$A_{Bj} = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad (1)$$

Table 2
9-Point Scale Used in Bayesian BWM

Linguistic variable	Code	Crisp value
Equally important	E	1
Equal to moderately more important	EM	2
Moderately more important	M	3
Moderately to strongly more important	MS	4
Strongly more important	S	5
Strongly to very strongly more important	SV	6
Very strongly more important	V	7
Very strongly to extremely more important	VI	8
Extremely more important	I	9

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D. Step 4. Generating the OW (Others-to-Worst) Vector

Similar to step 3, the OW vector is obtained by comparing each project to the worst project (Equation 2).

$$A_{jW} = (a_{1W}, a_{2W}, \dots, a_{nW})^T \tag{2}$$

E. Step 5. Obtaining the Optimal Group Weights of the Projects

Since both the BO and OW vectors consist of positive integers, they have the characteristics of a multinomial distribution w_j, w_W, and w_B represent the weights of projects j, W, and B, respectively; w_j, w_W, and w_B can be expressed as in Equations 3-5.

$$w_j \propto \frac{a_{jW}}{\sum_{j=1}^{n} a_{jW}}, \forall j = 1,2, \dots, n \tag{3}$$

$$w_W \propto \frac{a_{WW}}{\sum_{j=1}^{n} a_{jW}} = \frac{1}{\sum_{j=1}^{n} a_{jW}} \tag{4}$$

$$\frac{1}{w_B} \propto \frac{a_{BB}}{\sum_{j=1}^{n} a_{Bj}} = \frac{1}{\sum_{j=1}^{n} a_{Bj}} \Rightarrow \frac{w_B}{w_j} \propto a_{Bj}, \forall j = 1,2, \dots, n \tag{5}$$

The optimal weight for w_j can be obtained by employing statistical inference. However, since MCDM mandates that each weight should be non-negative and the sum of all weights must be equal to 1, we use the Dirichlet Probability Distribution (Equation 6) to construct the model and the associated function.

$$Dir(w|\alpha) = \frac{1}{B(\alpha)} \prod_{j=1}^{n} w_j^{\alpha_j - 1} \tag{6}$$

where α is the vector parameter.

1. Step 5.1. Constructing the Joint Probability Distribution for Group Decision-Making

Assuming that there are K experts, where $k = 1, 2, \dots, K$, and the optimal individual weight evaluated by each expert is w^k, the integrated group weight is represented as w_{agg}. The joint probability distribution of the group decision is found by

$$P(w^{agg}, w^{1:K} | A_B^{1:K}, A_W^{1:K}) \tag{7}$$

where $A_B{}^{1:K}$ represents the BO vector of expert k; and $A_W{}^{1:K}$ represents the OW vector of expert k.

2. Step 5.2. Developing the Bayesian Hierarchy Model

Considering the independence between the different variables, the joint probability of the Bayesian model is

$$P(w^{agg}, w^{1:K}|A_B^{1:K}, A_W^{1:K}) \propto P(A_B^{1:K}, A_W^{1:K}|w^{agg}, w^{1:K})P(w^{agg}, w^{1:K}) \quad (8)$$

And w^k under condition w^{agg} can be constructed as the Dirichlet distribution (Equation 9).

$$w^k|w^{agg} \sim Dir(\gamma \times w^{agg}), \forall_k = 1,2,\dots,K \quad (9)$$

where w^{agg} is the average value of the distribution; and γ is a non-negative parameter.

Finally, the group optimal weight w^{agg} obeys the Dirichlet distribution (Equation 10), and parameter α is set to 1.

$$w^{agg} \sim Dir(\alpha) \quad (10)$$

Once the probability distributions of all parameters are constructed, the posterior distribution can be calculated using the Markov-chain Monte Carlo (MCMC) technique. This calculation process only requires the BO and OW vectors provided by each expert to obtain the optimal group weight w^{agg}, accordingly.

For a more detailed explanation of Bayesian BWM and obtaining the statistical inference of all parameters, please refer to Mohammadi and Rezaei's (2020) study.

IV. DATA ANALYSIS

In this study, seven proposed projects were jointly developed by a decision-making team consisting of 32 experts. The experts were then interviewed again to ask them to select the most important and least important projects from these seven. To keep the experts from influencing each other, they were asked to fill out the questionnaire independently. Thus, the first expert believed that D_1 was the most important project and D_7 was the least important. Therefore, to obtain the BO and OW vectors for that expert, the other projects were compared the other projects to D_1 and D_7. The BO and OW vectors for all experts, as shown in Table 3 and Table 4, were obtained by following the same steps. The survey data from the 32 experts were collected for a period of almost two months, and the questionnaires underwent preliminary consistency testing, with an average consistency ratio of 0.0027, indicating a high level of consistency.

Table 3
The BO Vectors for All Experts

	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Expert 1	E	EM	M	M	E	M	M
Expert 2	E	EM	EM	E	E	EM	M
Expert 3	E	EM	S	E	E	EM	S
Expert 4	E	M	M	M	E	M	M
Expert 5	EM	M	M	M	E	M	M
Expert 6	E	EM	S	M	E	EM	S
Expert 7	E	M	EM	M	EM	M	EM
Expert 8	E	MS	EM	MS	E	MS	EM
Expert 9	EM	EM	EM	EM	EM	E	EM
Expert 10	E	S	S	MS	E	MS	E
Expert 11	E	I	S	E	E	MS	S
Expert 12	E	M	EM	EM	E	M	M
Expert 13	E	M	EM	M	E	M	EM

Expert 14	E	EM	S	MS	E	MS	EM
Expert 15	E	MS	EM	MS	E	MS	EM
Expert 16	E	EM	EM	EM	E	EM	EM
Expert 17	EM	I	S	E	E	MS	S
Expert 18	E	S	S	MS	E	MS	E
Expert 19	E	MS	MS	M	E	MS	MS
Expert 20	E	EM	S	E	E	EM	S
Expert 21	E	MS	E	M	E	MS	MS
Expert 22	E	I	S	E	E	MS	S
Expert 23	E	S	S	MS	E	MS	E
Expert 24	E	M	EM	M	E	M	EM
Expert 25	E	MS	EM	MS	E	MS	EM
Expert 26	E	EM	S	MS	E	MS	EM
Expert 27	E	M	EM	M	E	M	EM
Expert 28	E	M	M	M	E	M	M
Expert 29	E	S	S	MS	E	MS	E
Expert 30	E	I	S	E	E	MS	S
Expert 31	E	MS	EM	MS	E	MS	EM
Expert 32	E	M	EM	M	E	M	EM

Table 4
The OW Vectors for All Experts

	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Expert 1	M	EM	E	E	M	E	E
Expert 2	M	EM	EM	M	M	EM	E
Expert 3	S	M	E	S	S	M	E
Expert 4	M	E	E	E	M	E	E
Expert 5	EM	E	E	E	M	E	E
Expert 6	S	M	E	EM	S	M	E
Expert 7	M	E	EM	E	EM	E	EM
Expert 8	MS	E	EM	E	MS	E	EM
Expert 9	E	E	E	E	E	EM	E
Expert 10	S	E	E	EM	S	EM	S
Expert 11	I	E	EM	I	I	M	EM
Expert 12	M	E	EM	EM	M	E	E
Expert 13	M	E	EM	E	M	E	EM
Expert 14	S	M	E	EM	S	EM	M
Expert 15	MS	E	EM	E	MS	E	EM
Expert 16	EM	E	E	E	EM	E	E
Expert 17	SV	E	EM	I	I	M	EM
Expert 18	S	E	E	EM	S	EM	S
Expert 19	MS	E	E	EM	MS	E	E
Expert 20	S	M	E	S	S	M	E
Expert 21	MS	E	MS	EM	MS	E	E
Expert 22	I	E	EM	I	I	M	EM
Expert 23	S	E	E	EM	S	EM	S
Expert 24	M	E	EM	E	M	E	EM
Expert 25	MS	E	EM	E	MS	E	EM
Expert 26	S	M	E	EM	S	EM	M
Expert 27	M	E	EM	E	M	E	EM
Expert 28	M	E	E	E	M	E	E
Expert 29	S	E	E	EM	S	EM	S

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Expert 30	I	E	EM	I	I	M	EM
Expert 31	MS	E	EM	E	MS	E	EM
Expert 32	M	E	EM	E	M	E	EM

Following the Bayesian BWM procedure introduced in Section 3 and using the MATLAB software provided by Mohammadi and Rezaei (2020), the group weights of each project were obtained. The weights of D_1 to D_7 are 0.247, 0.08, 0.092, 0.124, 0.251, 0.095 and 0.11, respectively. The priority rank of project importance is D_5, D_1, D_4, D_7, D_6, D_3, and D_2.

Table 5

Individual Weights and Group Weights of the Projects

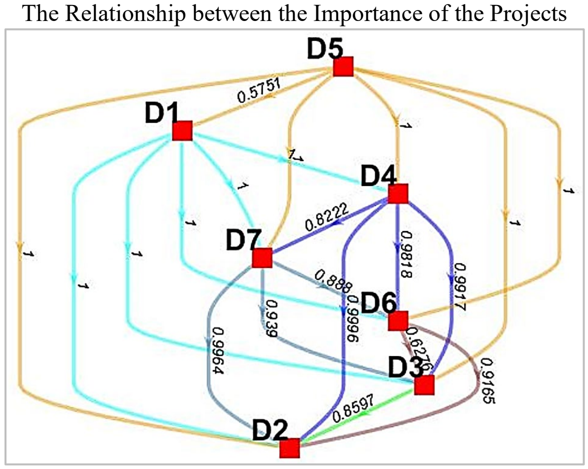
		D_1	D_2	D_3	D_4	D_5	D_6	D_7
$W^{1:k}$	Expert 1	0.247	0.089	0.091	0.120	0.252	0.094	0.107
	Expert 2	0.243	0.085	0.094	0.130	0.247	0.098	0.104
	Expert 3	0.245	0.089	0.082	0.136	0.249	0.101	0.098
	Expert 4	0.248	0.083	0.092	0.120	0.253	0.095	0.108
	Expert 5	0.242	0.084	0.093	0.121	0.254	0.096	0.109
	Expert 6	0.248	0.091	0.085	0.121	0.252	0.103	0.100
	Expert 7	0.247	0.082	0.098	0.120	0.244	0.095	0.115
	Expert 8	0.248	0.079	0.098	0.116	0.253	0.091	0.114
	Expert 9	0.239	0.084	0.094	0.124	0.244	0.104	0.111
	Expert 10	0.247	0.077	0.085	0.118	0.252	0.094	0.127
	Expert 11	0.250	0.066	0.087	0.146	0.254	0.095	0.101
	Expert 12	0.246	0.081	0.097	0.125	0.251	0.094	0.107
	Expert 13	0.246	0.081	0.097	0.118	0.251	0.094	0.114
	Expert 14	0.247	0.091	0.084	0.117	0.252	0.093	0.116
	Expert 15	0.248	0.079	0.098	0.116	0.253	0.091	0.114
	Expert 16	0.245	0.083	0.093	0.122	0.250	0.096	0.110
	Expert 17	0.239	0.067	0.088	0.148	0.257	0.097	0.103
	Expert 18	0.248	0.076	0.085	0.118	0.252	0.094	0.127
	Expert 19	0.250	0.081	0.090	0.124	0.255	0.093	0.106
	Expert 20	0.245	0.089	0.082	0.136	0.249	0.101	0.098
	Expert 21	0.247	0.079	0.107	0.122	0.251	0.091	0.103
	Expert 22	0.250	0.066	0.087	0.146	0.254	0.096	0.101
	Expert 23	0.247	0.077	0.085	0.118	0.252	0.094	0.126
	Expert 24	0.246	0.081	0.097	0.119	0.250	0.093	0.114
	Expert 25	0.248	0.079	0.098	0.116	0.253	0.091	0.114
	Expert 26	0.247	0.091	0.084	0.117	0.252	0.093	0.116
	Expert 27	0.246	0.081	0.097	0.119	0.250	0.093	0.113
	Expert 28	0.248	0.083	0.092	0.120	0.253	0.095	0.109
	Expert 29	0.247	0.077	0.085	0.118	0.252	0.094	0.127
	Expert 30	0.250	0.066	0.087	0.146	0.254	0.095	0.101
	Expert 31	0.249	0.079	0.098	0.116	0.253	0.091	0.114
	Expert 32	0.246	0.081	0.097	0.119	0.250	0.093	0.114
$W^{aggregation}$		**0.247**	**0.080**	**0.092**	**0.124**	**0.251**	**0.095**	**0.110**

To ensure the reliability of the generated ranking, we also conducted a credal ranking test using MCMC technique to calculate the average confidence level through multiple simulations. The results of the credal ranking test are presented in Table 6. It can be seen in the table that most of the project importance judgments are reliable, except for "D_5 with respect to D_1" and "D_6 with respect to D_3," which are slightly weak, with values of 51.51% and 62.76%, respectively. However, this does not affect the reliability of the overall evaluation results. The relationship between the importance of the projects is diagrammed more clearly in Figure 1.

Table 6
The Results of the Credal Ranking Test

	D_1	D_2	D_3	D_4	D_5	D_6	D_7
D_1	-	100.00%	100.00%	100.00%	-	100.00%	100.00%
D_2	-	-	-	-	-	-	-
D_3	-	85.97%	-	-	-	-	-
D_4	-	99.96%	99.17%	-	-	98.18%	82.22%
D_5	57.51%	100.00%	100.00%	100.00%	-	100.00%	100.00%
D_6	-	91.65%	62.76%	-	-	-	-
D_7	-	99.64%	93.90%	-	-	88.80%	-

Figure 1
The Relationship between the Importance of the Projects



In addition to conducting credal ranking tests, confirming expert consensus is also important. Figure 2 diagrams the individual project weights given by the 32 experts. When the consensus is better, the graph will show more converging lines. It can be inferred from this diagram that the experts in the decision-making group have a high degree of consensus and that there are no particularly divergent judgments. Some managerial implications based on the results of the Bayesian BWM analysis are discussed in Section 5.

V. DISCUSSIONS

MCDM is used to make decisions when faced with multiple objectives or criteria. It can help decision-makers make rational judgments between various choices. The value of MCDM in real-world industry decision-making is high because many of the decisions that have to made involve multiple objectives and considerations.

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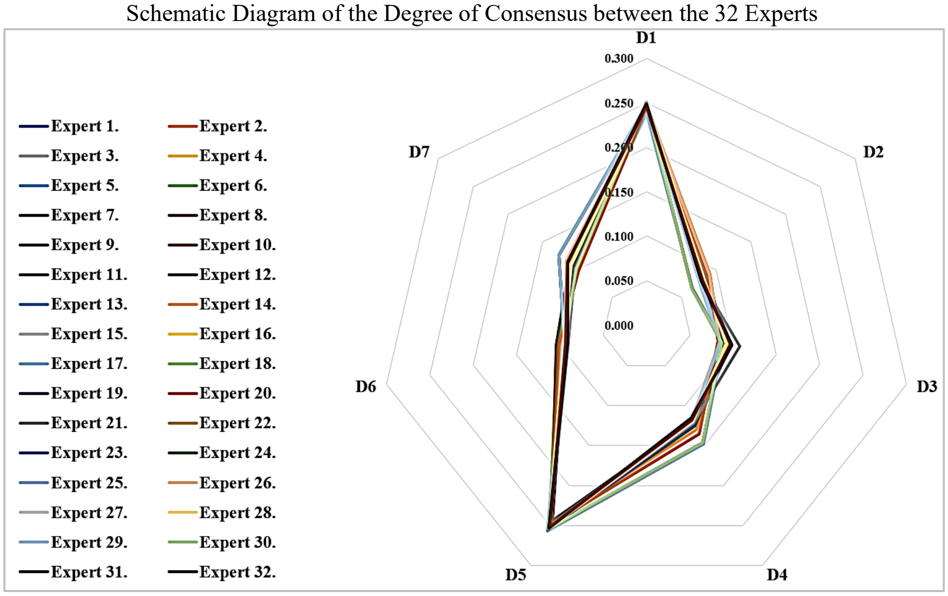
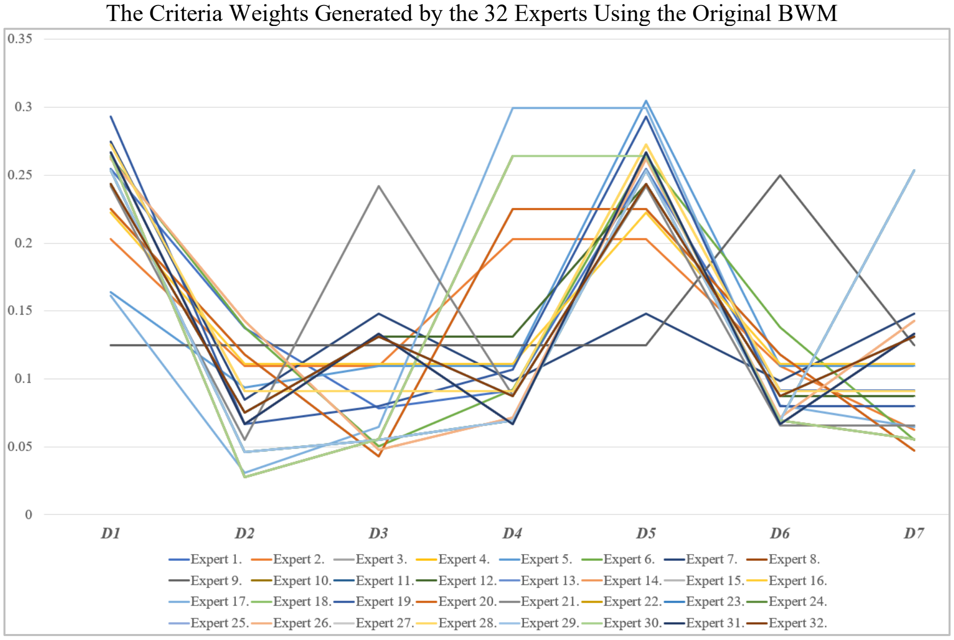
Figure 2
Schematic Diagram of the Degree of Consensus between the 32 Experts



Bayesian BWM technique is a practical and reliable method used to obtain subjective weights of criteria. It overcomes the limitations of the original BWM in effectively integrating the opinions of multiple experts. As shown in Figure 3, it can be observed that the criterion weights generated by 32 experts using the original BWM exhibit significant differences. That's why using the arithmetic mean to aggregate the opinions of 32 experts is not an appropriate approach, as it would eliminate the potential weight differences. Nowadays, many research studies have begun to use Bayesian BWM technique to replace the original BWM for analysis. For example, Saner et al. (2022) applied this technique to assess hospital preparedness in the face of disasters, Gul and Yucesan (2022) employed it to evaluate the performance of Turkish universities, and Ak et al. (2022) used it for occupational health, safety and environmental risk assessment.

From the Bayesian BWM analysis discussed in this paper, it can be concluded that technology selection (D_1) and evaluation of market competitiveness (D_5) are the two most important MCDM projects for successful digital transformation of enterprises. The evaluation of digital technology implementation in enterprises is very important because it involves the long-term interests and future development of the enterprise. There are several factors that must be considered in the selection of digital technology, including the determination of enterprise goals, assessment of implementation costs, risk avoidance, process reengineering, and employee education and training. In introducing digital technology, companies must clearly identify their goals and needs. Without clear objectives, investing in technology will only be a waste of time and money. On the other hand, technology adoption requires a significant amount of resources and time, and companies need to evaluate these costs to ensure that they can bear the burden and the risks. The Return on Investment (ROI) is the variable usually considered to determine whether the investment is worthwhile. Although digital transformation can bring many benefits to the company, there may also be resistance from employees due to changes in workflow or management systems. Therefore, transformation efforts must include comprehensive employee training to support the normal operations after technology adoption.

Figure 3
The Criteria Weights Generated by the 32 Experts Using the Original BWM



The evaluation of market competitiveness involves the consideration of multiple factors such as market size, market share, product quality, brand image, and so on. In digital transformation, data analytics and market research tools can assist businesses in evaluating these indicators and formulating digital transformation strategies based on the evaluation results. For example, companies can collect consumer feedback and comments through web crawlers and social media analytics tools to understand product quality and market feedback. At the same time, market analysis can provide information about market trends and competitor intelligence, helping businesses understand the market environment and their competitive situation. Companies that aim at digital transformation need to develop strategies that are suitable for themselves, based on the evaluation results of market competitiveness. For example, if the evaluation results show that product quality is insufficient, companies can take steps to improve product quality by introducing more advanced production technology and improved manufacturing processes. They can increase their market share against competitors releasing similar products by providing better after-sales service and expanding brand influence. The development of such strategies requires targeted development based on the evaluation results of market competitiveness.

In addition, the evaluation of market competitiveness can also help companies conduct risk assessment and management. In digital transformation, companies face a variety of risks including technological, security, and legal risks. Through the evaluation

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of market competitiveness though, companies can better understand the risks they must face and the opportunities in the market.

Although investment evaluation (D_2), risk management (D_3), cost-benefit analysis (D_4), measurement of customer experience and service quality (D_6), and recruitment of talent (D_7) are not the most important MCDM projects, their importance cannot be ignored. When we make decisions, improving one key performance indicator (KPI) may also have an impact on other KPIs; this is called interdependence. For example, if a company is doing well at recruiting talent and can attract high-quality employees to join the company, this will directly affect their business performance and product quality. On the other hand, if the company chooses to reduce production costs, this may lead to lower product quality, which affects customer experience and market share. Therefore, when conducting cost-benefit analysis, companies need to consider the interdependence between different criteria and develop comprehensive overall strategies to achieve long-term maximization of benefits.

VI. CONCLUSION

Digital transformation has become a necessary step in the development of global businesses today. Successful digital transformation can add significant business value and help companies attain competitive advantages. In order to improve operational efficiency and productivity, enterprises need to achieve high collaboration and improve automation through digital transformation among departments. The introduction of digital technology in production lines may shorten production cycles, reduce labor costs, and decrease time costs. Similarly, the application of data analysis technology can enable enterprises to better understand customer needs and market trends, and make more precise predictions for production and sales.

Bayesian BWM analysis not only allows the integration of judgments from multiple experts but also includes rigorous consistency, confidence, and consensus tests, making the analytical results more reliable. This study finds that technology selection (D_1) and evaluation of market competitiveness (D_5) are the two most important projects in promoting digital transformation for companies. They can significantly reduce the failure rate of digital transformation implementation for businesses.

In summary, the contributions of this study can be summarized as follows. Firstly, this method helps decision-makers understand the work projects in which MCDM can assist in promoting digital transformation. Secondly, this study identified the priority of these MCDM work items in digital transformation. Finally, some management implications were formulated as recommendations for promoting digital transformation.

- **Conflict of interest:** All authors declare that they have no conflict of interests.
- **Ethical approval:** This article does not contain any studies with human or animals performed by any of the authors.

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