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Evaluation and adoption of artificial intelligence in the retail industry

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Abstract

Purpose – The introduction of artificial intelligence (AI) technology has had a substantial influence on the retail industry. However, AI adoption entails considerable responsibilities and risks for senior managers. In this study, the authors developed an evaluation and selection mechanism for successful AI technology adoption in the retail industry. The multifaceted measurement and identification of critical factors (CFs) can enable retailers to adopt AI technology effectively and maintain a sustainable competitive advantage.

Design/methodology/approach – The evaluation and adoption of organisational AI technology involve multifaceted decision-making for management. Therefore, the authors used the analytic network process to develop an AI evaluation framework for calculating the weight and importance of each consideration. An expert questionnaire survey was distributed to senior retail managers and 17 valid responses were obtained. Finally, the Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) method was used to identify CFs for AI adoption.

Findings – The results revealed five CFs for AI adoption in the retail industry. The findings indicated that after AI adoption, top retail management is most concerned with factors pertaining to business performance and minor concerned about the internal system's functional efficiency. Retailers pay more attention to technology and organisation context, which are matters under the retailers' control, than to external uncontrollable environmental factors.

Originality/value – The authors developed an evaluation framework and identified CFs for AI technology adoption in the retail industry. In terms of practical application, the results of this study can help AI service providers understand the CFs of retailers when adopting AI. Moreover, retailers can use the proposed multifaceted evaluation framework to guide their adoption of AI technology.

Keywords Retail industry, Artificial intelligence (AI), Critical factors (CFs), Technology–organisation–environment (TOE) framework, Analytic network process (ANP), Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) method

Paper type Research paper

1. Introduction

Artificial intelligence (AI) is a rapidly growing technology, and the worldwide AI market is expected to be valued at US$15 tn by 2030 (PwC, 2020). The use of AI has considerable value in numerous industries, including the consumer product, corporate service, advertising, financial investment advice and media and entertainment industries. Notably, the industry that derives the highest output value from AI is the retail industry (Bughin *et al.*, 2018), which indicates that the application of AI in the retail industry can yield substantial benefits for retailers.

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In terms of AI applications in the retail industry, retailers should consider adopting strategies for AI-related data management to obtain solutions for business processes and value creation (Cao, 2021). Therefore, researchers have begun to explore text mining, chatbots, speech recognition, image recognition, data mining and machine learning techniques and have determined that the application of these AI tools is particularly beneficial for product pricing; promotion; customer service management and very important person analysis of marketing budget allocation, buyback time and consumer journey map value activities in retail areas (Chopra, 2019; Chen *et al.*, 2021; Gursoy *et al.*, 2019). The adoption of AI is crucial to retailers and many retailers have successfully adopted AI to enhance their competitive advantage (Trotter, 2018).

Despite the widespread acceptance of AI by companies, laggards who show no active use or adoption of AI remain (Weber and Schütte, 2019). According to a research report, 86% of top executives believe that their companies should introduce AI (PwC, 2020); therefore, regardless of the industry, executives often play a key role in the decision to adopt AI. Senior management pioneers in many businesses have integrated various AI applications into the regular operations of their companies, and many leadership teams are investing heavily in new AI initiatives. However, in Taiwan, the application of AI in the retail industry is still in its infancy (ComWea, 2020; PwC, 2020). AI service providers require an in-depth and multifaceted understanding of the adoption considerations and needs of the retail industry; such understanding can then guide their marketing promotion strategy. The retail sector has undergone drastic changes since the introduction of AI into it (Bedi *et al.*, 2022), and retailers must be mindful of the rapid development in the technology environment. Because of limited resources, businesses must carefully evaluate the adoption of AI technology and use a suitable mechanism to measure and evaluate the results of AI adoption. Despite the importance of AI for the retail industry, few studies have comprehensively examined critical factors (CFs) and performance measurement for successful AI adoption in the retail industry. AI service providers must understand the needs of retail enterprises and the key considerations for AI adoption with limited resources to allocate enterprise resources optimally in marketing strategies and encourage more retailers to adopt AI. Moreover, retail businesses can use CFs to reduce the failure risk of AI adoption. To expand the knowledge on AI application in the retail industry, we developed an evaluation framework and identified the CFs of AI adoption in Taiwan. For managers in the AI contractor and retail industry, having a clear understanding of the weight and importance of CFs affecting AI adoption can help reduce the potential for resource mismatches. Moreover, an enhanced understanding of the CFs of AI adoption can prompt retail managers to implement AI and increase the likelihood of successful AI adoption.

AI adoption is related to organisational innovation adoption. Numerous researchers have used the technology–organisation–environment (TOE) framework (Tornatzky and Fleischer, 1990) as a theoretical model in diverse innovative applications (e.g. Chen *et al.*, 2021; Pan *et al.*, 2022; Uwamariya and Loebbecke, 2020). From the perspective of organisational innovation adoption, the TOE framework is suitable for retailers to evaluate AI adoption. By focussing on a few CFs amongst numerous factors, businesses can increase the likelihood of successful technology adoption and can maintain normal operations. Therefore, we used the TOE framework and integrated the analytical network process (ANP) (Saaty, 1996) with the Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) method for determining acceptable advantage (Opricovic and Tzeng, 2004). These methods are multicriteria decision-making (MCDM) methods for effectively establishing an evaluation mechanism to analyse the weighting and ranking of factors and to confirm CFs. Thus, the aforementioned two methods were used for addressing the research problem.

2. Literature review

2.1 Artificial intelligence

The retail industry is facing changes in consumer behaviour resulting from rapidly changing technology, and technological developments in AI are radically altering retailing (Shankar *et al.*, 2021). Retailing is moving towards the establishment of a smart service system that integrates all people and things in the service process and consumer purchase willingness (Gursoy *et al.*, 2019). New technologies are constantly being developed for dramatically improving retailers' AI systems. AI refers to computing systems and covers many interlinked technologies, including data mining, machine learning, speech recognition, image recognition and sentiment analysis (Rodgers *et al.*, 2021). An AI system can continuously learn from and solve new problems in an ever-changing environment; the system leverages its constant data collection to achieve specific goals (Cao, 2021). AI is regarded as a modern analysis tool of consumer demand in the retail trade (Pillarisetty and Mishra, 2022), and AI systems are increasingly being deployed to influence customers' service experience (Yang *et al.*, 2022).

The availability of chatbots has a positive effect on customer experience and customer satisfaction. In particular, a need exists to predict future demand in marketing and inventory replenishment, and AI has achieved considerable progress in these areas through the efforts of industry and academia (Weber and Schütte, 2019; Chen *et al.*, 2021). Moreover, non-customer-facing AI applications can yield higher value than can customer-facing AI applications (Guha *et al.*, 2021). For example, Rodgers *et al.* (2021) highlighted the use of AI-based information systems utilising music as a biometric that can influence business decisions in organisations (Rodgers *et al.*, 2021).

2.2 Critical factors (CFs)

The concept of CFs was introduced by Daniel (1961), and CFs are elements that are essential for an organisation to survive and be successful. For survival in a highly competitive industry environment, understanding CFs has become a crucial management task for companies. Each company defines the CFs for its successful operation and survival according to industry type, organisation size or the adoption of innovative strategies. Thus, within an organisation, CFs can be regarded as a set of core competencies that ensure the organisation's competitive performance (Rockart, 1979). According to Leidecker and Bruno (1984), CFs refer to certain characteristics, conditions and factors that have a substantial effect on the competitiveness and survival of a particular industry.

2.3 TOE framework

The TOE framework was developed by Tornatzky and Fleischer in 1990. According to this framework, when an organisation considers adopting new information technology (IT), it should conduct a multifaceted evaluation of technological, organisational and environmental contexts to improve its operational performance and maintain a sustainable competitive advantage. Overall, TOE provides a clear analytical framework that can be used to examine influencing factors relating to the enterprises' adoption of innovative applications. Studies have employed TOE to investigate innovative Information System (IS) applications and Mobile Payment (MP) (Khan and Ali, 2018; Uwamariya and Loebbecke, 2020; Fu *et al.*, 2022).

However, few researchers have examined AI evaluation criteria and the CFs that affect AI adoption in retail from the perspective of organisational technology adoption and use. Therefore, we developed an evaluation framework and identified the CFs that affect the adoption of AI by retailers. This study uses TOE as a theoretical basis to examine the CFs for AI technology adoption in the retail industry to provide a foundational reference for retailers to evaluate and adopt AI technology successfully. Moreover, AI service providers can use CFs to understand retailers' major considerations to develop marketing strategies, satisfy business's needs and maintain strong partnerships.

3. Methodology

3.1 Analytic network process

Identifying the CFs that affect an enterprise's adoption of AI applications is an MCDM problem. The most common method for conducting MCDM is the analytic hierarchy process (AHP) (Saaty, 1980). In the AHP, CFs are assumed to be independent. However, in real-world contexts, a customary dependency and feedback relationship exists between these factors, which makes their associations increasingly complex. Therefore, Saaty (1996) proposed the ANP in the form of a network with a nonlinear structure. In this study, we used the ANP to obtain the weights of the factors that affect AI adoption in retailing. The VIKOR method for determining acceptable advantage (Opricovic and Tzeng, 2004) was employed to identify the CFs objectively. The aforementioned two MCDM methods were integrated using the steps described in the following text.

Step 1. Establish the hierarchical structure of the factors

On the basis of existing literature, the evaluation criteria that affect the decision-making for a problem are sorted. Subsequently, a hierarchical structure is established according to the context, criteria and subcriteria layers.

Step 2. Design the questionnaire

A pairwise comparison questionnaire is designed on the basis of the hierarchical structure obtained in Step 1. This questionnaire is used to compare the importance of two factors within the *same* layer. The questionnaire comprises independent and dependent questions. The evaluation scale is divided into nine symmetrical scales for pairwise comparisons (Saaty, 1980), taking values of 9/1 and 8/1, respectively . . . 2/1, 1, 1/2, 1/3 . . . 1/8 and 1/9.

Step 3. Establish the original matrix

After the questionnaires are collected, a pairwise comparison matrix can be derived from the obtained data. The pairwise comparison matrix is the ratio of pairwise comparisons between two factors. The questionnaire data can be converted into the upper-right triangular value of the paired comparison matrix a_{ij}. The lower-left triangular value is the reciprocal of the upper-right triangular value as expressed in the following formula:

$$\mathrm{A} = [a_{ij}] = \begin{bmatrix} 1 & a_{12} & \ldots & a_{1n} \\ 1/a_{12} & 1 & \ldots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \ldots & 1 \end{bmatrix}$$

Step 4. Calculate the eigenvalues

After the paired comparison matrix is established, the eigenvalues can be obtained through numerical analysis. The method of Saaty (1980) that involves normalising the geometric mean of the rows is employed to determine the eigenvalues. The relevant equation is as follows:

$$W_i = \left[\prod\nolimits_{j=1}^{n} a_{ij}\right]^{\frac{1}{n}} / \sum\nolimits_{i=1}^{n} \left[\prod\nolimits_{j=1}^{n} a_{ij}\right]^{\frac{1}{n}}, \mathrm{I}, \mathrm{j} = 1, 2, 3, \ldots\ldots, \mathrm{n}.$$

Step 5. Test consistency

To determine the appropriateness of the expert questionnaire, the eigenvalues are subjected to a consistency test. The relevant equation is as follows:

$$CI = (\lambda_{max} - n)/(n-1), CR = (CI/RI_n),$$

where CR is the consistency ratio, CI is the consistency index, λ_{max} is the maximised eigenvector of the paired comparison matrix, n is the number of criteria and RI_n is a random index whose values are listed in Table 1 (Aguarón and Moreno-Jiménez, 2003). After the values for CI and RI are obtained, the consistency test can be performed. In general, $CR < 0.1$ indicates that the judgement has acceptable consistency (Saaty, 1980).

n	3	4	5	6	7	8	9	10	11	12
RI_n	0.525	0.882	1.115	1.252	1.341	1.404	1.452	1.484	1.513	1.535

Table 1. Values of RI_n

Step 6. Calculate the weights and conduct normalisation

After the questionnaire data pass the consistency test, the weights of the independent and dependent factors for each questionnaire item are calculated using the AHP method. The ANP weights are obtained by multiplying the weights of the independent factors by the weights of the dependent factors. After the weights of all factors are calculated, these weights are normalised.

Step 7. Identify the CFs

The VIKOR method is used to identify CFs. Let Qi be the ith alternative ($i = 1, 2 \ldots j$) and j be the number of alternatives. Amongst all alternatives, $Q1$ is the most suitable solution, followed by $Q2$. If $TD \geq DQ$, the optimal solution Qi is the compromise solution, where $DQ = 1/(j-1)$ and $TD = Q(i+1) - Qi$ (Opricovic and Tzeng, 2004).

4. Establishment of a hierarchical table

We first established a three-layer hierarchical factor table based on the TOE framework according to the results of a literature review.

4.1 Technological context

4.1.1 Data.

(1) Difficulty of data acquisition: Murdoch (1990) reports that AI technologies can serve as comprehensive solutions for retailers. The easier acquiring relevant data are, the more an AI system can help the retailers that use it.

(2) Data usefulness: A company can use an AI technology more effectively if the data it collects are more applicable and relevant to its business (Grewal *et al.*, 2017).

(3) Data complexity: According to Alon *et al.* (2001), processing data with high complexity requires special software, more time and more extensive domain knowledge.

4.1.2 AI technology readiness.

(1) AI system compatibility: AI system compatibility is an important factor in decision-making (Premkumar, 2003).

(2) AI system usefulness: AI system usefulness is one of the main factors affecting whether a company will or should adopt an innovative technology (Saffu *et al.*, 2008).

(3) AI system reliability: System malfunctions, including system failure, data loss and connection interruptions, should be avoided (Alshawi *et al.*, 2011).

4.1.3 Cognitive benefit.

(1) Operational efficiency: The improvement of operational efficiency is a key factor that affects a company's decisions of innovative applications (Gruhn *et al.*, 2007).

(2) Decision-making quality: Innovative technologies can help customers make decisions and even increase their confidence in and satisfaction with the decisions they make (Grewal *et al.*, 2017).

(3) Customer value: AI can be used to collect customers' actual physical locations whilst they shop as well as to answer customers' questions (Grewal *et al.*, 2017).

4.2 Organisational context

4.2.1 Organisational readiness.

(1) IT maturity: According to Low *et al.* (2011), IT maturity is positively correlated with the willingness of a company to integrate a new technology.

(2) Departmental cooperation: Communication and collaboration amongst departments is crucial to the implementation of IT systems (Akkermans and Helden, 2002).

(3) Organisational change capability: Business process re-engineering (BPR) helps companies achieve their goals through organisational change, specifically by enhancing their capabilities by adopting of new technologies (Hammer, 1990).

4.2.2 Organisational characteristics.

(1) Organisational scale: Organisational scale can influence organisational innovativeness (Tornatzky and Fleischer, 1990).

(2) Organisational systems: Organisational systems play a major role in company's decisions regarding the integration of innovative technologies (Tan *et al.*, 2007).

(3) Innovation capacity: Companies that are proactive and innovative are often more willing to accept new IT systems (Frambach and Schillewaert, 2002).

4.2.3 Employee-related factors.

(1) Top management support: Top management support is a major factor affecting a company's decisions regarding the adoption of AI technologies (Lee and Kim, 2007).

(2) Employee awareness: A company's IT department's understanding of a new technology is a key factor affecting whether the company will adopt that technology (Wang *et al.*, 2010).

(3) Employee acceptance: Employee acceptance of new technologies strongly affects a company's decisions regarding the integration of AI (Huang and Rust, 2018).

4.3 Environmental context

4.3.1 Macroenvironments.

(1) Government support: The government can act as both an investor and a supporter (Kang and Park, 2012) by investing in companies' research and encouraging companies to engage in innovation.

(2) Laws and regulations: Government regulations and technology- and cost-based competition can influence a company's decisions regarding the integration of innovative technology (Kamal, 2006).

(3) National IT infrastructure: Infrastructure can influence a company's decisions regarding the integration of innovative technologies (Kamal, 2006).

4.3.2 Industrial environment.

(1) Competitive pressure: If a company feels the pressure from its competitors, it will be motivated to integrate new technologies into its operations (Kuan and Chau, 2001).

(2) Industry attributes: Industry attributes strongly influence a company's decisions regarding the adoption of new technologies (Huang and Rust, 2018).

(3) Industrial change: In a volatile, unstable and competitive market, companies are more easily motivated to adopt innovative technologies (Lin, 2006).

4.3.3 Enterprise environment.

(1) Return on investment: Companies are often willing to invest in their computing systems because doing so can increase their return of investment (Alshamaila *et al.*, 2013).

(2) Peer adoption: When facing the competitive pressure, companies often make some proactive decisions, such as adopting new technologies that enhance their competitive advantages (Picoto *et al.*, 2014).

(3) Differentiated capabilities: When the uncertainty of the industry environment is high, companies are more likely to be motivated to adopt innovative technologies to differentiate their capabilities (Gatignon and Robertson, 1989).

In the present study, we examined the literature on the aforementioned factors influencing the adoption of AI or innovative technologies to construct an appropriate 3 × 3 hierarchical factor table based on the TOE framework (Table 2).

Goal	Criteria	Subcriteria
Technology	Data	Difficulty of data acquisition
		Data usefulness
		Data complexity
	AI technology readiness	AI system compatibility
		AI system usefulness
		AI system reliability
	Cognitive benefit	Improving operation efficiency
		Improving the quality of decision-making
		Enhancing customer value
Organisation	Organisation readiness	Information technology maturity
		Departmental cooperation
		Organisation change capability
	Organisational characteristics	Organisational scale
		Organisational system
		Innovative capability
	Employee	Top management support
		Employee awareness
		Employee acceptance
Environment	Macro environment	Governmental support
		Laws and regulations
		National information technology infrastructure
	Industrial environment	Competitive pressure
		Industry attributes
		Industrial change degree
	Enterprise environment	Return of investment
		Peer adoption
		Building differentiated capabilities

Table 2. Hierarchical factors for factors of AI adoption in enterprises

5. Data collection and CFs identification

5.1 Data collection

We designed a pairwise comparison expert questionnaire on the basis of the hierarchical factor framework (Table 2). Taking "data" in the criteria layer as an example, the subcriteria layer contains three factors: difficulty of data acquisition, data usefulness and data complexity. We designed pairwise questionnaires with independent and dependent comparisons.

Because the ANP involves using expert questionnaires, we recruited senior experts to complete our study's questionnaire, thus obtaining optimal results. Therefore, we employed purposive sampling, which is a nonprobability sampling method where participants are selected according to the researcher's judgement. Researchers generally believe that they can obtain a representative sample through reasonable judgement (i.e. by using purposive sampling), thereby saving time and cost (Black, 2010).

According to Delbecq *et al.* (1975), a reasonable sample size for expert questionnaires is between 15 and 30. Accordingly, 17 managers (representing 17 of the top 20 retail chains in Taiwan) were invited to an expert meeting that involved face-to-face interviews. All 17 questionnaires were valid. The total annual output value of the participating companies exceeded 50% of the total output value of retail chains in Taiwan. Because all the interviewees were high-level managers and thus were likely to have deep knowledge of the industry, the 17 collected questionnaires could be used for follow-up research and analysis. Data from the returned expert questionnaires were tested for consistency. The *CI* and *CR* values were less than 0.1, which indicates an acceptable level of consistency.

The AHP was employed to calculate the weights of the factors by using the data collected from the questionnaires. Table 2 presents the data matrix obtained for the subcriteria layer of the "data" in the criteria layer when assuming the factors to be independent. Tables 3–6 present the data matrices for the subcriteria layer when assuming the factors to be dependent. The ANP weight matrix (Table 7) was obtained by multiplying the weight matrix of the dependent factors (3×3) by the weight matrix of the independent factors (3×1). In this manner, the weights of all factors could be determined and connected in series. Finally, the weights of all factors were normalised (Table 8).

5.2 CFs identification

From the 27 factors listed in Table 8, 12 important factors (with weights greater than 0.037) with an average weight of 0.037 (1/27) were identified. The remaining 15 factors were considered to be of minor importance. Most relevant studies have indicated that a reasonable number of CFs is between 4 and 6 (Janjić *et al.*, 2020; Moya and Camacho, 2021; Zarei and Iran, 2018). Therefore, in this study, we terminated the extraction when more than four CFs had been identified.

The VIKOR method involves finding the smallest optimal number from a set of alternatives; this approach was used to extract CFs from the 12 important factors. First, we converted the weights of the 12 important factors into break values as follows: $Breakvalue(i) = (Q1 - Qi)/(Q1 - Q12)$; for instance, break value (1) = (0.1136 − 0.1136)/(0.1136 − 0.0369) = 0 and break value (3) = (0.1136 − 0.0637)/(0.1136 − 0.0369) = 0.6506. The break values of the 12 important factors are presented in Table 9. By employing the aforementioned extraction principle, we obtained only one factor with $TD \geq DQ$ in the first extraction. The presence of only one CF (data usefulness) in the first extraction implied that fewer than four CFs would ultimately be obtained. For the second extraction, the factor with $TD \geq DQ$ was excluded. We observed no significant difference in the importance of the second and third factors: i.e. if $TD \geq DQ$ for the third factor in the next extraction, the second factor had to be extracted with the third factor. Thus, only one CF (data usefulness) was extracted in two extractions: i.e. fewer than four CFs were extracted. In the third extraction, TD was greater than or equal to DQ for the third, fourth and fifth factors. Because the third and second factors had to be extracted together, four CFs were selected in the third extraction. Thus, we obtained five CFs through three extractions, which satisfied the extraction termination condition. The five identified CFs were data usefulness, difficulty of data acquisition, AI system usefulness, organisational change capabilities and enhancement of customer value (Table 9).

	Difficulty of data acquisition	Data usefulness	Data complexity	Weights (AHP)
Difficulty of data acquisition	1.0000	0.9826	4.5053	0.4465
Data usefulness	1.0177	1.0000	4.5850	0.4544
Data complexity	0.2220	0.2181	1.0000	0.0991
λmax = 3.0073	R.I. = 0.5250	C.I. = 0.0037	C.R. = 0.0070 $\leqq$ 0.1	

Table 3.
Pairwise independence questionnaire

	Difficulty of data acquisition	Data usefulness	Data complexity	Weights (AHP)
Difficulty of data acquisition	1.0000	1.3397	3.8170	0.4979
Data usefulness	0.7465	1.0000	2.8492	0.3717
Data complexity	0.2620	0.3510	1.0000	0.1304
λmax = 3.0894	R.I. = 0.5250	C.I. = 0.0447	C.R. = 0.0851 $\leqq$ 0.1	

Table 4.
Weights for whether the difficulty of data acquisition is the most important

	Difficulty of data acquisition	Data usefulness	Data complexity	Weights (AHP)
Difficulty of data acquisition	1.0000	3.5621	7.7948	0.0910
Data usefulness	0.2807	1.0000	2.1883	0.7097
Data complexity	0.1283	0.4570	1.0000	0.1992
λmax = 3.0963	R.I. = 0.5250	C.I. = 0.0481	C.R. = 0.0917 $\leqq$ 0.1	

Table 5.
Weights for whether data usefulness is the most important

	Difficulty of data acquisition	Data usefulness	Data complexity	Weights (AHP)
Difficulty of data acquisition	1.0000	2.0329	2.1434	0.2512
Data usefulness	0.4919	1.0000	1.0543	0.2382
Data complexity	0.4666	0.9485	1.0000	0.5106
λmax = 3.0026	R.I. = 0.5250	C.I. = 0.0013	C.R. = 0.0025 $\leqq$ 0.1	

Table 6.
Weights for whether data complexity is the most important

6. Results analysis

In Table 9, there are five CFs obtained through the methodology proposed in this study. The CF analysis, practice contributions, management implications, academic contributions and strategic thinking are provided below.

6.1 CF analysis

The five CFs identified in this study are described in the following text in the order of their importance.

6.1.1 CF 1: data usefulness. AI adoption requires the collection of large quantities of data, and useful information must be obtained to have application value. If data usefulness is low, the AI system exhibits difficulty in providing valuable results and making a major

Table 7.
Weights calculation of ANP

Subcriteria of data in criteria layer	Weights for whether the factors are dependent: Difficulty of data acquisition (Table 4)	Data usefulness (Table 5)	Data complexity (Table 6)		Weights for whether the factors are independent (Table 3)		Weights of ANP
Difficulty of data acquisition	0.4979	0.0910	0.2512	x	0.4465	=	0.2886
Data usefulness	0.3717	0.7097	0.2382		0.4544		0.5121
Data complexity	0.1304	0.1992	0.5106		0.0991		0.1993

Table 8.
Weights of all factors in the hierarchical framework

A: Goal layer (weight)	B: Criteria layer (weight)	C = A × B	D: Subcriteria layer (weight)	E = C × D
T(0.5027)	T1 (0.4413)	0.2218 (1)	T11 (0.2886)	0.0640 (02)
			T12 (0.5121)	0.1136 (01)
			T13 (0.1993)	0.0442 (11)
	T2 (0.2597)	0.1306 (4)	T21 (0.2357)	0.0308 (17)
			T22 (0.4878)	0.0637 (03)
			T23 (0.2765)	0.0361 (13)
	T3 (0.2990)	0.1503 (3)	T31 (0.3088)	0.0464 (10)
			T32 (0.3103)	0.0466 (09)
			T33 (0.3810)	0.0573 (05)
O (0.3033)	O1 (0.5311)	0.1611 (2)	O11 (0.3020)	0.0487 (08)
			O12 (0.3191)	0.0514 (06)
			O13 (0.3788)	0.0610 (04)
	O2 (0.3304)	0.1002 (6)	O21 (0.3204)	0.0321 (16)
			O22 (0.3227)	0.0323 (15)
			O23 (0.3569)	0.0358 (14)
	O3 (0.1386)	0.0420 (8)	O31 (0.5242)	0.0220 (19)
			O32 (0.2695)	0.0113 (24)
			O33 (0.2063)	0.0087 (26)
E (0.1940)	E1 (0.5992)	0.1162 (5)	E11 (0.4315)	0.0501 (07)
			E12 (0.3179)	0.0369 (12)
			E13 (0.2507)	0.0291 (18)
	E2 (0.2445)	0.0474 (7)	E21 (0.4376)	0.0207 (20)
			E22 (0.3007)	0.0143 (22)
			E23 (0.2618)	0.0124 (23)
	E3 (0.1564)	0.0303 (9)	E31 (0.5200)	0.0158 (21)
			E32 (0.1914)	0.0058 (27)
			E33 (0.2887)	0.0087 (25)

Table 9. CFs extraction for AI adoption in retailing

CFs $Q(i)$	Weights	1st extraction: Rank (i)	1st extraction: Break value(B_i)	1st extraction: $TD=(B_{i+1}-B_i)$	1st extraction: $TD \geq DQ$, $DQ = 0.083$	2nd extraction: Rank (i)	2nd extraction: Break value(B_i)	2nd extraction: $TD=(B_{i+1}-B_i)$	2nd extraction: $TD \geq DQ$, $DQ = 0.091$	3rd extraction: Rank (i)	3rd extraction: Break value(B_i)	3rd extraction: $TD=(B_{i+1}-B_i)$	3rd extraction: $TD \geq DQ$, $DQ = 0.1$
Data usefulness	0.1136	1	0.0000	0.6467	yes								
Difficulty of data acquisition	0.064	2	0.6467	0.0039	no	1	0.0000	0.0111	no				yes
AI usefulness	0.0637	3	0.6506	0.0352		2	0.0111	0.0996		1	0.0000	0.1007	yes
Organisation change capability	0.061	4	0.6858	0.0482		3	0.1107	0.1365		2	0.1007	0.1381	yes
Enhancing customer value	0.0573	5	0.7340	0.0769		4	0.2472	0.2177		3	0.2388	0.2201	yes
Inter-departmental cooperation	0.0514	6	0.8110	0.0169		5	0.4649	0.0480		4	0.4590	0.0485	no
Governmental support	0.0501	7	0.8279	0.0183		6	0.5129	0.0517		5	0.5075	0.0522	
Information technology maturity	0.0487	8	0.8462	0.0274		7	0.5646	0.0775		6	0.5597	0.0784	
Improving the quality of decision-making	0.0466	9	0.8735	0.0026		8	0.6421	0.0074		7	0.6381	0.0075	
Improving operation efficiency	0.0464	10	0.8761	0.0287		8	0.6494	0.0812		8	0.6455	0.0821	
Data complexity	0.0442	11	0.9048	0.0952		10	0.7306	0.2694		8	0.7276	0.2724	
Laws and regulations	0.0369	12	1.0000			11	1.0000			10	1.0000		

Note(s): 1: DQ = 1/(n−1)

contribution to retailers. Thus, if the data and information acquired through AI adoption are useful for retailers, improved operational performance should ensue.

6.1.2 CF 2: difficulty of data acquisition. Because structured and unstructured data are distributed across various corporate departments and external websites (open data), considerable resources are required for data acquisition. Furthermore, collecting data on consumers' complete shopping journey (including consumer data generated by competitors) is challenging. An enhanced method or tool that facilitates the collection of complete data would add considerable value for retailers.

6.1.3 CF 3: AI system usefulness. AI system usefulness can maximise the value of AI systems. If AI system usefulness is high, the optimised AI model constructed after data collection should increase the value of retail customers and benefit the business performance of the retailer.

6.1.4 CF 4: organisational change capabilities. Organisations must have the ability to use innovative models to enhance their competitive advantage and achieve their strategic goals; that is, they must have the ability to change (e.g. through corporate culture enhancements, organisational re-engineering, modifications in the overall thinking of staff and ability enhancement) to apply AI effectively and realise the substantial benefits derived from its adoption.

6.1.5 CF 5: enhancement of customer value. AI applications can have a marked impact when customers shop in physical or virtual stores. Such applications include those providing innovative services, such as the analysis of customer data for precision marketing. Retailers can also develop relevant operational and marketing strategies based on consumer questions and suggestions, thereby enhancing customer value. Therefore, the augmentation of customer value (customer loyalty and satisfaction) is a CF influencing AI adoption in retailing.

6.2 Practice contributions

6.2.1 Need for increased attention to internal controllable factors. In terms of the context layer, members of top management believe that the CFs affecting AI adoption in retailing in the TOE framework are those related to the technological and organisational contexts. Notably, none of the CFs identified in this study are related to the environmental context. This finding might be attributable to the organisational and technological contexts involving factors that can be controlled within the enterprise; by contrast, environmental factors tend to be uncontrollable external factors. Thus, retailers consider internal controllable factors to be more important than external factors. Consequently, managers should focus particular attention on internal controllable factors.

6.2.2 Need for increased attention to factors of business performance. From the perspective of technological maturity, although some scholars have highlighted AI system compatibility, AI system usefulness and AI system reliability as important factors, we found that AI system usefulness is an especially CF. Our findings suggest that AI system compatibility and AI system reliability are related to system functionality, whereas AI system usefulness affects business performance and results in augmented external benefits. Therefore, retailers seem to attach higher importance to factors that can improve business performance than to those that ameliorate system functional efficiency.

6.2.3 Special importance of customer value with regard to internal operational efficiency. In terms of cognitive benefits, scholars have asserted that improvements in work efficiency, decision-making quality and customer value are crucial factors that affect the adoption of innovative applications. We posit that operational efficiency and decision-making quality are CFs affecting internal operations and that augmenting customer value is particularly beneficial for business performance. From the perspective of top management's emphasis on strategy, the finding that factors that affect business performance have higher importance than those that affect operational efficiency seems reasonable.

6.2.4 Organisational ability to adapt to new business models. In terms of the organisational context, scholars have identified factors such as organisational scope, top management and organisational change capability as important factors that affect the adoption of innovative applications. In this study, organisational change capability was one of the CFs in the organisational context. Thus, we conclude that only organisations with change capability can effectively adopt the innovative operating model of AI applications and realise the corresponding benefits.

6.3 Theoretical implications

Studies have explored the willingness of consumers to use AI technologies from the perspective of consumer purchase behaviour (Gursoy *et al.*, 2019; Yang *et al.*, 2022; Pillarisetty and Mishra, 2022). However, few studies have examined the matters related to AI adoption from the perspective of organisational adoption decisions. How businesses with limited resources can optimally evaluate and adopt AI for retail management is thus a topic that merits examination. To fill this research gap, we developed a multifaceted evaluation framework and then examined the CFs of AI adoption in the retail industry by using hybrid MCDM methods.

In the highly competitive retail business environment, AI selection and adoption has become a major concern for management. From an organisational technology adoption perspective, understanding which considerations have the strongest influences on AI adoption in retail is imperative. Therefore, the main contribution of this study is the development of a multifaceted evaluation framework and the identification of CFs for AI adoption by using a hybrid MCDM approach. The proposed framework can serve as a basis for future research and as a reference for AI selection and adoption in other industries.

Furthermore, we identified five CFs that affect AI adoption in retail, all of which are focussed on the technological and organisational contexts. From the perspective of the 80/20 rule (Koch, 2011), on the basis of CFs, AI service providers can understand which evaluation considerations have the strongest effect on AI adoption in retail. Moreover, our empirical results might aid businesses in the retail industry in successfully adopting AI technology.

6.4 Managerial implications

We developed an assessment framework for AI adoption in retail and identified 5 critical, 7 important and 15 minor factors that can help organisations adopt AI. AI service providers with limited resources should allocate their resources to the five CFs that retailers deem most important according to the relative weights of these factors. Any spare resources can be allocated to the next 7 important factors and the remaining 15 factors. Such a systematic empirical approach can help retailers use their resources more effectively to adopt AI technology successfully. AI can be used by retailers to improve management performance. Tasks such as customer behaviour analysis, sales forecasting and inventory management can be facilitated through the use of AI. With the increased use of AI, the accuracy of goods distribution management between retailers and distributors can be improved.

As AI service providers strive to facilitate the adoption of AI by retailers, they must be mindful of the needs and considerations of retailers, not simply the technical aspects of AI. AI service providers can help retailers and dealers change their business models to meet the necessary conditions for AI adoption. Business process re-engineering solutions can play a key role in AI adoption for the creation of innovative business models.

Because of information asymmetry, many retailers today still lack sufficient knowledge and information on AI adoption and are, therefore, concerned about failure when adopting this technology. To reduce the risk of failure when retailers adopt AI, AI service providers must provide the necessary support for retailers wishing to adopt AI. Therefore, in addition to a strong focus on the five CFs, AI providers should prioritise ongoing communication, education and training for retailers to reduce retailers' risk of failure in AI adoption.

Finally, retailers must have the ability and willingness to adapt to the innovative business models offered by AI to increase their competitive advantage and performance through resilient supply chain (distribution) management. Useful data and optimised AI models are required to enable AI to make a meaningful contribution to the retail industry. Therefore, when adopting AI, retailers should carefully consider the CFs that affect business performance. The findings of this study might help improve organisational decision-making quality and technology-optimised resource allocation.

6.5 Strategic thinking

The value of AI technologies lies in their capacity to enhance a company's ability to differentiate its capabilities and obtain immediate feedback from internal and external customers. According to the five CFs identified in this study, we draw the following conclusions regarding strategic thinking before AI adoption, during AI adoption and after AI adoption.

6.5.1 Enhancement of customer value (before AI adoption). In an era of highly personalised costumer experiences, retail as a service has emerged as a major trend. When customers purchase goods in physical stores, retailers can collect the data of individual customers and use AI technology to perform personalised analysis and prediction. AI technologies can be integrated with voice assistants (chat bots) to display popular products in physical stores to enhance customers' experiences and must be able to provide customers with seamless services before, during, and after a purchase.

6.5.2 Organisational change capability (during AI adoption). Organisational change capability often involves whether able to propose the innovative business models through cross-departmental collaboration. Therefore, a company must enhance its organisational capability and adjust its cross-organisational collaboration processes and functions with customer value as its main focus. When necessary, organisational restructuring and institutional innovation, as well as changes in the company mindset or culture, can be implemented to facilitate the operation of new AI-based business models.

6.5.3 Digital transformation and the importance of information security (after AI adoption). In addition to bringing business value to enterprises, AI systems can be used as infrastructure for digital transformation. Besides, information security is not a CF in this study. This may be because the top executives of retail enterprises tend to focus on data acquisition and enhancing customer value in the early stages of AI adoption. However, as AI technology becomes more common in the retail industry, information security cannot be ignored. Therefore, retailers must develop comprehensive information security strategies after adopting AI technologies.

7. Conclusion

This study examined the CFs that affect AI adoption in retail. Five CFs were identified: data usefulness, the difficulty of data acquisition, AI system usefulness, organisational change capability and enhancement of customer value. We found that after AI adoption, top management in retailing prioritised factors related to business performance, such as enhancing customer value. By contrast, they tended to overlook factors related to internal operational efficiency. In addition, in AI adoption, top management prioritised internal controllable technical and organisational factors – such as data usefulness, the difficulty of data acquisition, AI usefulness and organisational change capability – over external uncontrollable environmental factors. Finally, we observed that top management support was not especially important because the respondents were top managers who could lead decision-making and did not require approval from a higher level of management. Therefore, the finding that top management focusses more on factors that influence business performance and internal controllable factors than on external uncontrollable factors is reasonable. Our findings might serve as a tactical reference for retailers, helping them to increase their willingness to adopt AI in retail, reduce the risk of failure in AI adoption and maximise the contribution of AI to business performance. By considering the CF weights identified in this study, businesses can decrease the possibility of resource misallocation.

However, at present, senior executives in Taiwan's retail industry can only express their views on the adoption of AI technologies in the retail industry when AI technologies, talent cultivation and related infrastructure are not yet mature. The findings of our study yielded five CFs related to technology and organisational structure. These CFs were identified as such by Taiwanese senior executives with a preliminary understanding of AI. However, previous studies have demonstrated that the environmental context also influences companies' decisions regarding the adoption of new technologies; therefore, studies conducted in different environments should yield different results. For example, in the early stage of AI adoption, senior executives may not consider information security to be a CF because of the limited availability of relevant data. As the scope of the applications of AI expands and retailers collect more data, information security may become a CF. Therefore, in the future, researchers can conduct studies on AI adoption in different environments, such as in different countries and in industries with different attributes, and compare their results with those of the present study.

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