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Enhancing the Competitiveness of AI Technology-Based Startups in the Digital Era

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Abstract: Artificial Intelligence (AI) startups possess four key attributes; being small enterprises, adopting AI technology, undergoing digital transformation, and using big data systems to enhance their competitiveness. This study aims to identify the key influencing factors needed to enhance the competitiveness of AI technology-based startups and to suggest a decision-making model to improve the technology and business competitiveness of AI startups in the digital era. To achieve this, the hierarchy concept framework was built with four evaluation areas based on the mechanism-based view theory, and the 16 evaluation factors that can influence were identified through existing literature, combining factors related to the digital transformation, technological application, and business competitiveness of the startups. These factors were analyzed using the Analytic Hierarchy Process (AHP) by the survey, targeting experts in South Korea. The analysis results indicate that the subject area was the most crucial for the business competitiveness of AI startups. It was also revealed that the subject's strategic mind is the most significant factor to AI startups' success. In the case of two control groups, categorized as 'AI experts' and 'startup experts', AI experts chose the subject as the most important area, whereas startup experts selected the environment, and significant differences were observed in all other factors. The results of this study will provide implications for strengthening the business competitiveness of AI startups and factors important for the growth of AI startups in this era.

Keywords: AI; startups; decision-making model; mechanism-based view; AHP

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1. Introduction

Recently, many companies have pursued digital transformation strategies, reinforcing their workforce and services to incorporate digital technology (Borges et al. 2021; Regina and De Capitani 2022). Furthermore, as part of the endeavor to ensure the success of digital transformation strategies, the establishment of AI-based business models is expanding (Verhoef et al. 2021). AI technology, which includes natural language processing, machine learning, and deep learning, offers extensive and diverse data analysis capabilities across multiple industries, providing convenience in business management, planning, and operations (Kasemsap 2017).

As a result, the reliance on AI technology within companies is progressively increasing. The adoption of AI technology for business innovation is rapidly accelerating (Kitsios and Kamariotou 2021). Consequently, value chains through AI technology have become an essential factor that companies must consider (Feroz et al. 2021). Despite the increasing demand for the adoption of AI, many companies are still experiencing many trial-and-error attempts due to a lack of understanding of the difficulties involved in successfully adopting AI technology (Loureiro et al. 2021).

Although digital transformation strategies may vary by industry, securing data and obtaining the necessary technology to utilize it effectively are common requirements (Schwertner 2017). Due to these essential elements, such as data, as companies increasingly rely on AI, their operations tend to depend on data accordingly. There are numerous documents related to AI and business; however, there is limited research on the factors necessary for successfully utilizing AI within companies (Alsheibani et al. 2018). The forms and sizes of companies vary, and they are typically divided into several stages characterized by a series of events (Garnsey 1998).

Moreover, since 2020, artificial intelligence has emerged as a future growth engine, and global attention is now focused on AI startups. In recent years, artificial intelligence technology, poised to have widespread ripple effects across industries worldwide, has emerged as the core of future businesses. Consequently, countries and companies have significantly increased their investment in AI startups (Lisa et al. 2020).

CB Insights Report (2023) reported that the total financing of the world's top 100 AI startups was estimated at $10.1 billion, and that the market grew to 48% in 2023 compared to 2022. Of the top 100 companies, 77 are U.S. companies, with six AI startups from China, the U.K., and Israel each belonging to the leading group. In particular, among the world's top 100 AI startups, 11 are evaluated as unicorns, meaning unlisted startups with a corporate value of more than $1 billion, including 5 in China, 5 in the U.S., and 1 in the U.K. In addition, by sector, enterprise technology was the largest with 33, and AI startups are active in all industries, including healthcare, automation, semiconductors, administrative, financial, and industries, retail, laws, media, and agricultural and real estate (Sreenivasan and Suresh 2023a).

In general, AI startups seek to create economic value for companies through M&A, with global big tech companies such as Google and Apple. However, in order for AI startups to become unicorn companies independently and strengthen their market competitiveness, they need technology as well as independent business models and management strategies for sustainable growth (Font-Cot et al. 2023).

The success factors related to startups and those associated with driving digital transformation have each been subjects of extensive individual studies. However, success factors are not merely a collection of various individual factors but are expected to represent a significant intersection of importance for all. For instance, certain success factors for startups may potentially impede the success of AI, leading to possible conflicts between these two sets of factors. In this study, our objective is to comprehensively and holistically consolidate and examine these factors that have been individually scrutinized, with the aim of revealing the underlying common success factors. Therefore, this study aims to comprehensively identify important factors in AI startup competitiveness and present specific implications for AI startups to consider to corporate competitiveness based on the analysis results through the decision-making framework based on AHP. With social changes centered on AI technology, the role of AI startups is becoming more and more emphasized. The results of this study will provide meaningful implications for strengthening business competitiveness to experts of AI startups, as the continuous technological capabilities development and corporate growth of AI startups should be considered in this era's environment.

2. Literature Review

2.1. Influence Factors for Enhancing AI Technology-Based Startup Competitiveness

There are many definitions of startups in the literature (Omri et al. 2015; Blank and Dorf 2020; Sreenivasan and Suresh 2023b). Kakati (2003) identifies that a startup is a temporary organization that creates innovative products or services using advanced technology. Gimmon and Levie (2010) define it as dynamic and flexible companies that evolve with the market. OECD (2016) describes startups as innovative companies that address current issues by developing new business models. Fundamentally, startups have the potential for rapid growth within a short period at low costs and are renewable and expandable temporary organizations (World Economic Forum 2020; Gimmon and Levie 2010).

These diverse definitions highlight that startups are characterized by their innovation, adaptability, and potential for rapid growth. They cannot be classified based solely on size or longevity, underscoring the absence of a universally agreed-upon definition for startup companies. Therefore, startups are typically considered as a subgroup of various innovative companies, primarily characterized by their early-stage development and often small scale. This description aligns with the characteristics of AI startups (Omri et al. 2015). Digital transformation is not just the mere digitization of existing data. It represents a fundamental shift in the systems underpinning business and economic operations (Kim et al. 2021). From a similar perspective, an AI technology-based startup is characterized not simply by its use of digital technology as a component, but by its reliance on digital technology for its core business and fundamental competencies.

In examining the general, core enhancing factors for AI startup competitiveness, we found various insights from different studies. For instance, Brem (2008) emphasizes the importance of the entrepreneurial mindset, including a willingness to take risks and the desire to be a part of a business. Additionally, experience in the industry is considered a key factor for success. Regarding innovation-related research, Skawińska and Zalewski (2020) identifies crucial success factors such as the possession of specific expertise, the degree of differentiation from other opportunities, and structured processes. In addition, Bers et al. (2009) highlighted market insight, entrepreneurial spirit, and effective business structure and planning as essential elements for success, whereas Groenewegen and de Langen (2012) identify three core success factors for startups requiring fundamental innovation: an entrepreneurial mindset, a thorough business plan, and successful initial investment acquisition, as well as a focus on innovations that can benefit potential customers.

Santisteban et al. (2021) identified 27 significant success factors extracted from the literature. Similarly, Chen (2019) identified common factors affecting the successful adoption of AI technology. Song et al. (2008) suggested widely researched factors for new ventures. From the identified success factors, the authors extracted eight significant common factors, including supply chain integration, market scope, company age, startup team size, financial resources, founder's marketing experience, founder's industry experience, and the presence of patents. This previous literature identified the important factors: founder's R&D experience, founder's previous startup experience, environmental dynamics, environmental diversity, competitive intensity, etc. Chatterji et al. (2019) also found that companies that actively provided external advice to their employees had a 10% lower failure rate and a 28% higher growth rate compared to those that did not.

Research examining whether investing in research funding truly benefits venture firms' performance is noteworthy. According to Dowling and McGee (1994), their study revealed a positive correlation between research expenditure and a company's performance, aligning with the general perception. In contrast, Bloodgood et al. (1996) presented findings that contradicted prior research, suggesting a negative correlation between research expenditure and a company's performance and indicating that research funding might be detrimental. On the other hand, Zahra and Bogner (2000) concluded that there was no significant correlation between research funding and a company's performance. Their study did not find a statistically significant relationship between the two variables.

Although many previous studies defined innovation as a key success factor for technology-based startups, one indicated that venture firms concentrating on innovation had a 3-year survival rate of 56%, lower than the 63% survival rate of firms not emphasizing innovation (Hyytinen et al. 2015). Chen and Zhu (2008) found that higher levels of education among startup entrepreneurs positively influenced aspects like a company's growth and employee satisfaction.

Meanwhile, ethical aspects in the business decisions and strategic planning of startups are being extensively researched in works (Eitel-Porter 2021; Sloane and Zakrzewski 2022; Bessen et al. 2022) The importance of ethical considerations in the development and application of AI is gradually gaining prominence. Merhi (2023) split 19 factors into four categories: organization, technology, process, and environment. It was revealed that within these categories, technology emerged as the most crucial factor, and among the 19 factors examined, ethics was identified as the most important one. Sevilla-Bernardo et al. (2022) identified the success factors of startups as identifying idea, CEO's leadership, and business model. Kelly et al. (2022) examined common factors underlying the acceptance of artificial intelligence across various industries, including perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy.

2.2. Mechanism-Based View and Business Competitiveness

Business strategies were discussed from the perspectives of subject, environment, and resources individually (Westley and Mintzberg 1989). First, the subject-based perspective focused on the success factors of a company attributed to the exceptional capabilities of top management. They considered the process by which top management formulates and influences the company's business strategy as a critical success factor (Child 1972). Decisive decision makers with ultimate authority in establishing and determining organizational strategies were regarded as core success factors (Hannan and Freeman 1977).

On the other hand, the environment-based perspective, examining the success factors of a company from the standpoint of the surrounding environment, is called the environmental-based perspective. Several documents have regarded the environment as a key factor in a company's success (Porter 1997). The literature typically categorizes corporate environments into three main types. Firstly, industrial organization theory primarily focuses on the structure, behavior, and performance of industries (Rodrigue et al. 2013). Organizational ecology theory views organizational adaptability as rapidly changing environments, observing the process of organization creation, development, and dissolution (Scott 2013). Institutional theory considers corporate activities as decision-making processes intended to minimize uncertainty and secure legitimacy in the surrounding environment (Wernerfelt 1984). On the other hand, the resource-based perspective argues that a company's success is determined more by the unique resources it possesses internally than by subjects or the environment. This perspective explains that a company's core competencies within its organization serve as a source of competitive advantage (Hamel and Prahalad 1994; Lee and Koo 2008). However, the perspective that examines a company's business strategy from the three perspectives of subject, company environment, and the resources it possesses has clear limitations in describing companies that exhibit performance beyond a certain level (Cho and Lee 1997). According to this approach, each company can have different proportions and priorities of subject, environment, and resources, or it can utilize mechanisms between these elements to achieve competitiveness and exert its unique competitiveness as a mechanism (Cho and Jung 2004).

The mechanism-based view, as a model that analyzes the dynamics of the subject, environment, and resource, connected by mechanisms, can be seen as a concept that integrates the subject, environment, and resource-related research into strategic theory (Kim and Kim 2022). Even if two companies have similar capabilities in terms of their executives, compete within the same industry, and even have the same level of resources and internal capabilities, the interaction between the subject, environment, and resource; how they are combined; and what proportions and sequences they have will lead to completely different mechanisms being created, thus resulting in different outcomes.

In the SER-M model, the mechanism is a factor that intricately influences management strategies and activities through the organic interaction between subjects, the environment, and resources. The mechanism can be described as a core capability that strategically shapes the characteristics and rarity of a company's valuable resources (Zollo and Winter 2002). The SER-M model has been widely used as a tool to comprehensively analyze corporate strategies. The mechanism perspective emerged from the need for a dynamic theory that explains the long-term success of a company, as opposed to a single static factor among subjects, the environment, and resources affecting the competitiveness of a company at a specific point in time (Hamel and Prahalad 1994; Cho and Lee 1997). It highlights the development of a company's competitive advantage over time based on the dynamic nature of these elements.

3. Method

3.1. Research Framework and Variables

When examining prior research on the critical factors of technology-based startups, various studies have taken different approaches (Chatterji et al. 2019; Binowo and Hidayanto 2023). Skawińska and Zalewski (2020) categorized factors into the domains of innovation, organization, and entrepreneurship for comparison. Binowo and Hidayanto (2023) suggested factors according to the developmental stages of companies, dividing them into pioneering, growth, and expansion phases, and conducted comparative analyses for each growth stage. This study belongs to a category that prioritizes factors within specific domains. To mitigate bias and ensure a more balanced approach, this study introduced the inclusion of various factors affecting AI startup competitiveness by the SER-M framework, incorporating research from three distinct domains: startups, AI technology adoption, and digital transformation. By doing so, this study provided empirical evidence of the critical factors for AI startups without favoring any specific category.

As shown in Table 1, from the existing literature, a total of 16 factors related to the success of startups and the successful adoption of AI and digital transformation within the SERM framework were extracted. To enhance the objectivity and reliability of these factors in this AHP study, a Delphi interview was conducted with experts. The participants; 'tech leader of Google Korea', 'AI leader of Kookmin Bank', 'Director of Acryl Inc.', 'research director of AI Research Institute Inc.', and 'CTO of Coupang' in the Delphi interviews all have at least 15 years of experience in the AI business. These include CEOs of AI startups, leaders in AI technology from global companies, department heads responsible for AI in large companies, and directors of AI research institutes. As a result, the six factors were condensed into four factors as per SERM: Subject, Environment, Resource, and Mechanism, yielding a total of sixteen factors divided into the four areas of SERM, as depicted in Figure 1.

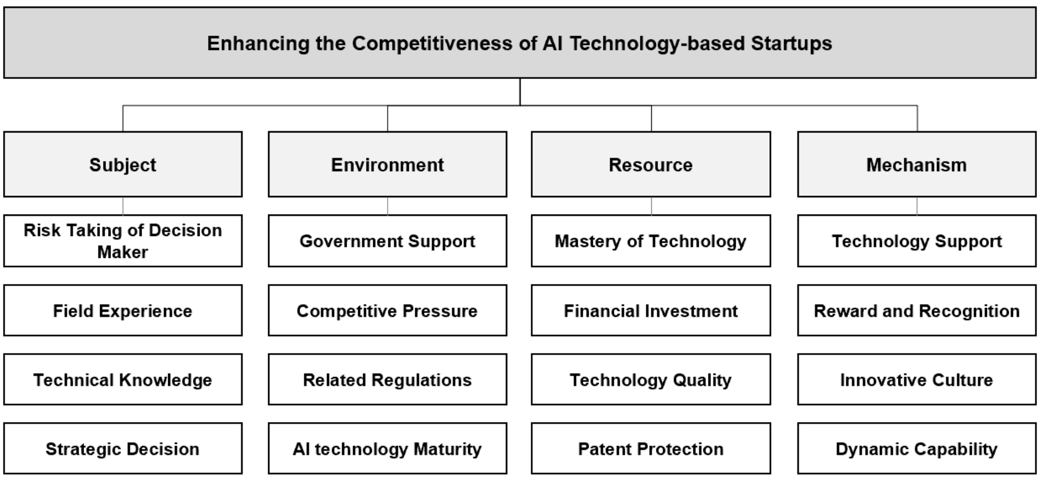

Figure 1. Research framework.

Table 1. Evaluation factors and definition.

Evaluation Area	Evaluation Factor	Definition	Related Literature
Subject	Risk-taking of decision maker	Willingness and actions to take the risk of the final decision maker	(Brem 2008) (Groenewegen and de Langen 2012) (Song et al. 2008) (Binowo and Hidayanto 2023) (Lizarelli et al. 2022) (Oakey 2003) (Sevilla-Bernardo et al. 2022) (Abubakar et al. 2018)
	Field experience	CEO experience and proficiency in industry and technology	
	Technical knowledge	CEO's technical knowledge and level of learning and information	
	Strategic decision	Strategic and clear decision making for CEO's technical management and business activities	
Environment	Government support	Government support in terms of financing and environment	(Yan and Mercado 2023) (Chen 2019) (Pugliese et al. 2016) (Fenwick et al. 2018) (Chorev and Anderson 2006)
	Competitive pressure	Competitive pressure to drive development	
	Related regulations	Restrictions or supports in terms of related regulations	
	AI technology maturity	Preference towards AI technology in terms of investing	
Resource	Mastery of technology	Company has resources that possess sufficient technical experience and professional knowledge mastery of technology of employees	(Lammers et al. 2022)
	Financial investment	Raise seed funding then raise additional rounds of capital until exit or acquisition	(Robinson and McDougall 2001) (West and Noel 2009) (Al-Fraihat et al. 2020) (Marino and De Noble 1997)
	Technology quality	Set of inherent characteristics or properties of products and/or services that meet the needs of customers and allow a company to achieve business success	
	Patent protection	Availability of firm's patents protecting product	
Mechanism	Technology support	Managerial support for developer's activity	(Chen 2019) (Delgado-Verde et al. 2016) (Corrales-Estrada 2019) (Gobena and Kant 2022) (Arora et al. 2020)
	Reward and recognition	Reasonable and proper reward and recognition	
	Innovative culture	Ability to identify opportunities and obtain resources that can transform opportunities into successful ventures	
	Dynamic capability	Ability of organizations to integrate and build internal and external competencies that quickly address changing market conditions and systematically solve problems	

3.2. AHP Analysis Method

AHP is a decision-making technique that was developed by Saaty in 1972. It involves organizing multiple attributes into hierarchies and determining the importance of each attribute to select the optimal alternative. This methodology is used to measure the relative importance of non-quantified factors and to assess logical consistency in decision-making.

The AHP method utilizes the knowledge, experience, and intuition of evaluators to derive key factors through surveys and assess their relative importance by conducting pairwise comparisons in order to construct a decision hierarchy (Udo 2000). In this study, an efficient AHP method was employed to determine the importance of various success factors affecting AI companies. The relative importance of each factor was calculated based on the geometric mean of the evaluations. Additionally, CI and CR were generated to assess reliability and validity, ensuring consistency in the responses.

To briefly summarize the AHP method presented by Saaty (1972), for a set of n factors, they first conduct pairwise comparisons, resulting in $n(n-1)/2$ comparisons to evaluate each factor on a scale from 1 to 9. For instance, when comparing item a_i to item a_j (1 <= i,j <= n), if a_i is considered superior to a_j with a score of k (1 <= k <= 9), the matrix element a_{ij} is assigned the value of k, and a_{ji} is set to 1/k. This process results in the formation of the following matrix A of all the comparison scores, where the diagonal elements always equal 1 since they represent self-comparisons.

$$A = \begin{bmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ 1/a_{1n} & \cdots & 1 \end{bmatrix} \tag{1}$$

After finding the primary eigenvalue of this comparison score matrix, the Consistency Ratio (CR) is calculated using the following formula.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

$$CR = \frac{CI}{RI} \tag{3}$$

In this equation, λ_{max} represents the primary eigenvalue of a comparison score matrix, and n is the number of factors being compared. The denominator *RI* stands for Random Index, and its values are predefined based on the matrix size. If the calculated value is less than 0.1, it is generally considered a consistent response, and in some cases, it can be considered consistent if it is less than 0.2.

Each response goes through a normalization process to calculate weights and assess their relative importance. To calculate the relative importance, we need to first calculate the geometric mean along each row of the matrix and then normalize it. Let H_j represent the geometric mean of row *j* of matrix A, which is calculated as follows.

$$H_j = \left(\prod_{i=1}^{n} a_{ji}\right)^{1/n} = \sqrt[n]{a_{j1}a_{j2}\ldots a_{jn}} \tag{4}$$

Therefore, if we denote the normalized weight of factor k among n factors as W_k, W_k is calculated as follows.

$$W_k = H_k / \sum_{i=1}^{n} H_i, \tag{5}$$

To aggregate the final research results from the survey, only responses with a consistency ratio (CR) of less than 0.1 were adopted from the total responses. After this process, 15 responses from Group A and 15 responses from Group B were used, totaling 30 responses.

3.3. Research Process and Data Collection

The survey method chosen for this study was the AHP, for which a questionnaire was designed with a focus on pairwise comparisons to represent the model. The survey was conducted from 1 October to 20 October 2023. It targeted two groups, the AI expert group and the startup expert group, and was administered through offline and online interviews. Detailed instructions were provided to aid participants' understanding of the survey. In case of online, the survey was conducted using a Microsoft Word document format, which was distributed and subsequently collected via email. Additionally, all necessary authorizations were obtained for the interviews during this process.

Interviews and surveys were conducted with the consent of the survey subjects to collect data. Based on Articles 33 (secret protection, etc.) and 34 (duty of statistical workers, etc.) of the Statistical Act of the Republic of Korea, it was conditional not to disclose information name and personal information. The use of the questionnaire was allowed on the condition that the research results were shared and survey data were not used other than in this study.

'AI expert group' consisted of AI experts who worked for AI startups or dedicated AI departments of large companies. 'Startup expert group' was composed of general experts, including CEOs of regular companies, management professionals, business school professors, and IT-related professors. Both groups were made up of professionals with at least 10 years of experience. General experts also included individuals with a strong connection to AI and startups. The distribution of respondents is presented in Table 2.

Table 2. Demographic information.

Section	Characters	Frequency	Ratio (%)
Gender	Male	21	70
	Female	9	30
Age	40s	10	33
	50s	20	67
Work Experience	10–20 Y	4	13
	20–30 Y	26	87
Professional Area	AI Expert	15	50
	Startup Expert	15	50

4. Results

4.1. Analysis Result of Evaluation Variables

The consistency rate (CR) of the individual factors of subject, environment, resource, and mechanism were 0.059, 0.037, 0.043, and 0.034, respectively. These values indicate appropriate consistency. Table 3 presents the average, maximum (Max), minimum (Min), and median values of the CR for each response.

Table 3. Results of overall CR values.

CR Values	Subject	Environment	Resource	Mechanism
Average	0.059	0.037	0.043	0.034
Max	0.098	0.089	0.092	0.098
Min	0	0	0	0
Median	0.065	0.038	0.043	0.022

Table 4 and Figure 2 provide a summary of the overall results. As shown in Table 4, the most critical factor in the evaluation area was the subject, with a weight of 0.399. This weight was approximately 2.6 times higher than the least weighted factor, mechanism (0.155). This result suggests that the significance of top management in small-scale enterprises like startups is highly emphasized. The second most important factor was the environment (0.225), followed by resources (0.221) in the third position.

Within the subject domain, strategic decision (0.409) appeared as the most critical factor, followed by technical knowledge (0.301), risk-taking of decision maker (0.146), and field experience (0.144). In the environmental domain, when looking at the specific factors, the area of AI technology maturity (0.415) for AI stood out as remarkably important. Subsequently, respondents emphasized the significance of related regulations (0.205), competitive pressure (0.200), and government support (0.180).

Table 4. Weights and priority of evaluation variables.

Evaluation Areas	The Weights of Areas	Evaluation Factors	The Weights of Evaluation Factors			
	Local		Local *	Priority	Global **	Priority
Subject	0.399	Risk-taking of decision maker	0.146	3	0.054	7
		Field experience	0.144	4	0.047	9
		Technical knowledge	0.301	2	0.120	2
		Strategic decision	0.409	1	0.179	1
Environment	0.225	Government support	0.180	4	0.035	14
		Competitive pressure	0.200	3	0.050	8
		Related regulations	0.205	2	0.043	11
		AI technology maturity	0.415	1	0.097	3
Resource	0.221	Mastery of technology	0.271	3	0.060	6
		Financial investment	0.279	2	0.063	5
		Technology quality	0.356	1	0.078	4
		Patent protection	0.094	4	0.019	16
Mechanism	0.155	Technology support	0.233	4	0.028	15
		Reward and recognition	0.286	1	0.041	12
		Innovative culture	0.240	3	0.040	13
		Dynamic capability	0.242	2	0.045	10
Total	1.000		4.000		1.000	

* Local: mean value of evaluation factors in each group of criteria. ** Global: mean value of evaluation factors in total criteria.

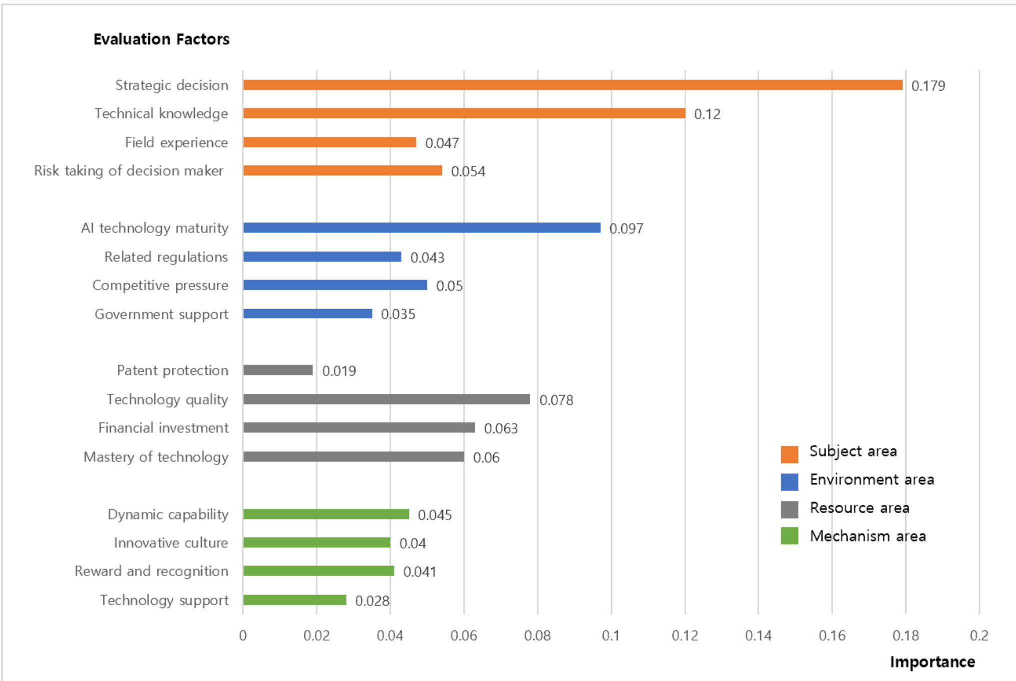

Figure 2. Importance analysis result of evaluation factors by areas.

The most crucial factor was technology quality (0.356). This was followed by the mastery of technology of employees (0.271) and financial investment (0.279), with patent protection (0.094) having the lowest level of importance among these factors. In the mechanism domain, the primary factor was identified as rewards and recognition (0.286). Following this, dynamic capability (0.242), an innovative culture (0.240), and support from the technology support (0.233) ranked in decreasing order of importance.

Furthermore, when the importance of each domain was reflected within the factors and the overall ranking of these factors was examined, the most critical factor of the 16 was the strategic decision of the subject (0.179). Following this, the subject's field experience (0.120) was the second-most crucial factor. In contrast, patent protection in the resource domain (0.019) emerged as the least important of the 16 factors. It is important to note that government support (0.035) in the environmental domain and technology support (0.028) in the mechanism domain ranked 16th and 15th, respectively, indicating their relatively low importance.

4.2. Comparison between the Evaluation Areas by the Groups

When comparing the responses between the AI experts' group and the startup experts' group, we revealed some similarities, as well as distinct differences. Initially, both groups identified the subject as the most important factor. However, their responses differed significantly when it came to the next most important factors. The results are displayed in Table 5.

Table 5. Comparison analysis result on evaluation areas.

Evaluation Areas	The Weights of Areas			
	AI Expert Group		Startup Expert Group	
	Importance	Priority	Importance	Priority
Subject	0.568	1	0.231	3
Environment	0.106	4	0.344	1
Resource	0.208	2	0.234	2
Mechanism	0.119	3	0.191	4
Total	1.000		1.000	

For AI experts, the subject (0.568) was overwhelmingly the most important, followed by resources (0.208), mechanism (0.119), and environment (0.106), in terms of importance. In contrast, startup experts rated the environment (0.344) as the most important, followed by resources (0.234), subject (0.231), and mechanism (0.191). The differences in importance among these four factors were not as significant in the startup experts' responses compared to those of the AI experts, and for subject and resources, the importance ratings were nearly identical.

4.3. Comparison between the Evaluation Factors by the Groups

When comparing the responses of the two groups regarding the 16 overall factors, a noticeably different pattern emerged. AI experts considered strategic decision (0.270) as the most important, whereas startup experts rated favorable investment target, meaning relative AI technology maturity (0.157), as the most crucial. Furthermore, AI experts ranked the importance of the factors as follows: technical knowledge (0.166), technology quality (0.074), and risk-taking of decision maker (0.067), the top three factors being related to the subject. In the case of startup experts, the most important factor was "favorable investment targets" (0.157), followed by strategic decision (0.088), technology quality (0.083), and competitive pressure (0.078). The factor patent protection earned the ranking of 15th place, with a score of 0.022, from AI experts, whereas it was ranked the lowest—16th place, with a score of 0.017—by startup experts, indicating it was the least important factor (see Table 6).

Table 6. Comparison analysis result on evaluation factors.

Evaluation Factors	The Weights of Evaluation Factors				Priority of Factors (by Global)	
	Local		Global			
	AI Expert Group	Startup Expert Group	AI Expert Group	Startup Expert Group	AI Expert Group	Startup Expert Group
Risk-taking of decision maker	0.121	0.170	0.067	0.040	4	13
Field experience	0.119	0.168	0.065	0.029	6	14
Technical knowledge	0.274	0.329	0.166	0.074	2	5
Strategic decision	0.486	0.333	0.270	0.088	1	2
Government support	0.208	0.151	0.020	0.049	16	12
Competitive pressure	0.188	0.212	0.022	0.078	14	4
Related regulations	0.244	0.166	0.025	0.061	13	7
AI technology maturity	0.360	0.470	0.038	0.157	8	1
Mastery of technology	0.237	0.306	0.047	0.072	7	6
Financial investment	0.278	0.280	0.065	0.061	5	8
Technology quality	0.373	0.338	0.074	0.083	3	3
Patent protection	0.112	0.076	0.022	0.017	15	16
Technology support	0.302	0.164	0.030	0.027	10	15
Reward and recognition	0.249	0.322	0.028	0.055	11	9
Innovative culture	0.217	0.263	0.026	0.054	12	11
Dynamic capability	0.232	0.251	0.035	0.055	9	10
Total	4.000	4.000	1.000	1.000		

5. Conclusions

5.1. Discussion and Implications

As a result of the study, AI technology-based startups found that the subject's activities had the greatest impact on corporate competitiveness. In particular, strategic decisions were found to have a more important impact than anything else, and both AI and startup expert groups confirmed this to be the most important factor. In the end, in the case of AI technology-oriented startups, it was confirmed that the leadership and decision-making of the subjects that lead the business beyond basic product or service competitiveness such as technology and data will determine the victory or defeat of the company. Just as previous studies have emphasized the importance of CEO entrepreneurship and leadership, AI startups, like other general startups, confirmed that the subject's strategic decision-making is important.

Especially in the case of artificial intelligence business environments, it is necessary to respond flexibly to very rapid technological advances and market trend changes, and accordingly, a company's business competitiveness can be maintained or sustained by fast and accurate decision making. In the end, it is important to develop technology to respond to changes in the artificial intelligence industry and ecosystem, but it can be seen that the strategic response ability of those in charge is important.

In the case of the AI expert group, the subject was selected as the most important factor, in first place, but in the case of the startup expert group, the subject was selected as the last factor, in third place. On the other hand, in the case of the startup expert group, the environment was selected as the most important influencing factor, but the AI expert group ranked the environment as the third priority, showing a very contrasting difference. This clearly shows the difference between AI experts with a strong technology development perspective and startup experts with a strong business perspective.

In the end, environmental factors such as markets and regulations affect AI-related business most sensitively, but in terms of technology development, a strategic approach to what technology development and commercialization will be achieved may be important. Conflicts and cooperation between technical and organizational perspectives in business activities within a company have been an issue of continuous management, as discussed in previous studies (Landers and Marin 2021; Chapman 2006). In the end, it was confirmed that AI startups also need a business management system that allows for rational and strategic cooperation and coordination, considering both the technology development perspective and the organizational and business perspective.

Both groups selected 'technology quality' as an important competitive factor. In the end, in the case of AI startups, it was confirmed that acquiring unique AI technology quality in the competitive market is the most important factor because the competitiveness of products and services based on AI technology is differentiated from AI technology quality. As Schwertner (2017) pointed out, the competitive market for artificial intelligence technology is rapidly evolving. Accordingly, it can be clearly confirmed that constant technology development and quality maintenance can lead to business success. Moreover, startup experts suggested the maturity of artificial intelligence technology as the most important factor. This indicates that having mature artificial intelligence technologies that can be commercialized in the market rather than developing new technologies can be a more important prerequisite for business competitiveness.

Finally, artificial intelligence technology startups tend to focus on developing artificial intelligence technology. As can be seen from the research results, it was found that although technology quality is an important factor, direct technology factors such as technology support and patent protection are not important factors. In the case of artificial intelligence technology-based companies, business activities in the market are linked only when unrivaled and advanced technology is developed. They tend to focus on technology development because they may lose their competitiveness if continuous technology development is not made in line with rapid technological change. However, as research shows, it should be considered that just as much as technology development, organizational activities that can balance technology and business activities through strategic decision-making about the business in line with the market environment and trends can also be important.

5.2. Research Limitations and Future Plans

This study has limitations regarding the SERM framework used to extract factors evenly and to avoid biases. Future research could delve deeper into either the subject or environment, depending on the research subjects or objectives, in order to strengthen the in-depth analysis. Furthermore, performing similar studies using different categories other than SER-M and comparing the changes in the importance of various factors would provide valuable insights. On the other hand, this study was limited to South Korean AI technology-based startups. It may face clear limitations in terms of generalizing these factors to other regions with distinct economic and regulatory environments. As a future research agenda, creating separate frameworks that consider various economic and regional conditions and corresponding factors could enable more diverse studies to be conducted in different business environments.

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