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Priority Analysis Study for Digital Talent Nurturing Policy Projects

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Abstract

To propose directions for digital talent nurturing policies, this study classified existing government projects and analyzed their priorities through surveys of educational institutions and industry experts, revealing that school–company collaborative education—especially joint problem-solving projects—should be prioritized despite differing preferences between institutions and companies, and based on AHP results and expert interviews, it recommended expanding support for corporate-linked education to address qualitative talent mismatches, while emphasizing that government-level institutional improvements and university-centered policies are essential to resolve quantitative talent shortages.

Keywords : digital talent nurturing policy, AHP, Data analysis

Priority Analysis Study for Digital Talent Nurturing Policy Projects

1. Research Background

The global COVID-19 pandemic has led to a surge in demand for remote business solutions, accelerating digitalization across all industries, which in turn has driven remarkable growth in the SW.ICT sector. According to an analysis by the Software Policy & Research Institute (SPRi) of quarterly revenue data from software companies from 2008 to 2021, the software industry has shown consistent growth, reaching a record quarterly revenue of approximately 10 trillion KRW in the fourth quarter of 2021 (Hwang & Yoo, 2023).

As digital transformation accelerates, countries worldwide are formulating strategies to enhance their digital technology competitiveness and proactively address market demands and industrial structure changes (Kim, 2022). Reflecting this shift, the demand for digital specialists is increasing not only in IT companies but also in general businesses. A report by Amazon Web Services predicts that South Korea will need 227 million workers skilled in digital technologies by 2025. However, the supply of SW professionals is failing to meet this demand. The 2022 survey by the MOTIE showed that at the end of 2021, there was a 3.3% increase in the shortage of industrial technology personnel compared to the previous year, totaling 37,667, with the shortage rate in the SW sector at 4.3%, exceeding the overall industry average of 2.2%. Additionally, the growth rate of SW personnel has continued to decline over the past five years, from a 4.3% increase in 2017 to just 1.1% in 2021. This indicates a persistent and deepening quantitative mismatch in the domestic SW sector.

Major countries are actively developing and implementing national-level strategies for digital talent development. The U.S., since 2019, has been enhancing STEM education and developing AI curriculum guidelines under initiatives like the AI Initiative Executive Order and the National AI Research and Development Strategy. China established its Next Generation AI Development Plan in 2017, followed by the Zhilong X Plan in 2019, creating AI departments and interdisciplinary integrations to train AI masters and PhDs, and developing AI platforms and non-degree courses. Japan launched a comprehensive AI strategy in 2019, strengthening adult education to introduce AI-related job training (SPRi, 2021).

In response, the Korean government has been striving to lay the foundation for ICT talent development in the digital transformation era since 2019, with initiatives like the AI Graduate School, K-Digital Training programs. It has promoted digital education policies such as the AI and SW Education Expansion Plan (August 2020) and the AI Era Education

Policy Directions and Key Tasks (November 2020). The recently announced joint digital talent development plan by the MOE, MSIT, MOTIE, MOEL, MSS aims to cultivate 1 million digital talents—160,000 basic (high school and associate degree), 710,000 intermediate (bachelor's), and 130,000 advanced (master's and doctoral) level talents—through public-private cooperation from 2022 to 2026 (August 2022).

While the government's support for digital talent development in line with industry demand is commendable, most current initiatives are likely extensions or continuations of existing policies. Given the necessity for large-scale talent development and the industry's need for quantitative supply, maintaining and expanding existing policies is a rational approach. However, to enhance efficiency, it's crucial to prioritize which of the ongoing policy support projects should receive focused attention.

To set the goals for talent development policies, it's essential to differentiate between quantitative and qualitative aspects of trained talent, define how much and what level of talent should be developed, and determine the educational methods required. Setting these goals should ideally be based on the perspective of the final demand side, i.e., businesses, and address the longstanding gap between industrial and educational sectors by incorporating educational institutions' views for a balanced policy direction. At the 2022 Spring Conference of the Korea of Society Service, Minseok Lee, Dean of the

Innovation Academy, identified the lack of industry-academia linkage programs and differing learning methods between schools and the field as root causes of the qualitative limitations of domestic SW developers. This highlights a persistent qualitative mismatch in meeting the practical demands of the industry, despite the absolute shortage of digital personnel. According to SPRi's survey on AI/SW talent industry retraining, new hires often fall short of the practical skills required by the industry, even when hiring master's and doctoral graduates whose academic knowledge is high but practical skills are lacking (Kim, 2022). Interviews with industry stakeholders reveal that, regardless of educational background, an internal OJT period of 6 months to a year is necessary for practical work readiness (2021, SPRi).

These issues are not new and have been long-standing challenges in education policy, where conflicting interests and varied opinions naturally arise due to differing values, environmental conditions, and needs. Similarly, government digital talent support projects range from long-standing to newly attempted initiatives, with diverse methods and approaches. However, given the constraints of limited budgets and organizational capacity, especially in talent development projects where quick results are not feasible, it is necessary to prioritize and select policies for focused implementation. As previously mentioned, policy decision-making is complicated by differing perspectives and values, particularly evident in talent development where distinct views between educational institutions and industry have persisted, complicating decision-making. Therefore, it is essential to base decisions on quantitative data to supplement qualitative opinion gathering and provide objective evidence for decision-making.

In conclusion, this study aims to classify the various digital talent development support policy projects currently pursued by the government, gather opinions from industry and educational institution stakeholders, and measure the relative importance of each support policy project. While previous studies on digital talent development policies have addressed macro-level policy support directions or frameworks, there has been a lack of research on specific support projects or methods. This study seeks to present a practical direction for digital talent development support policies by classifying and prioritizing existing or ongoing specific policy support projects and providing evidence-based solutions for resolving stakeholder conflicts in the policy decision-making process.

2. Literature Review

2.1 Research on Digital Talent Development Policy

Research on digital talent development policies in Korea can be categorized into studies that propose responses to the emergence or growth of new industries and those that address issues and suggest improvements in overall talent development policies.

With the IT venture boom following the advent of the internet in the early 2000s, the demand for IT personnel surged. Research highlighting the need for high-level software engineering talent for IT industry development analyzed SW engineering bachelor's and master's programs at foreign universities and proposed specific curricula for domestic university programs to cultivate such talent (Bae, 2001). With the emergence of immersive media, the importance of the digital content industry has been emphasized. Research proposing specialized talent development policies for new ICT industry technologies highlighted the need for systematic and consistent processes in digital content industries and education, the acquisition of foreign technologies, and education in human-tech, establishing a new educational framework for differentiated capabilities (An & Choi, 2015). Kim (2018) addressed the growth of the sports IT industry and the shortage of personnel by categorizing policy evaluation criteria for sports IT specialists into technical, economic, and socio-political factors, emphasizing the urgency of securing technical capabilities as the most critical factor. As artificial intelligence emerged as a core technology in the digital industrial ecosystem, research on AI.SW talent development began. Analyzing major domestic companies' AI.SW education programs, conducting surveys with companies, and holding expert roundtables, researchers assessed the current status and policy needs for AI and SW education. They suggested policy improvements, including tailored talent development and supply strategies by company size and the establishment of job-specific training programs (Song et al., 2021). Research analyzing domestic AI.SW talent development policies using awareness analysis examined the characteristics of policy processes, identified policy tools and objectives through input-output analysis, and demonstrated that AI application and diffusion across industries could drive digital transformation, corporate growth, and job creation (Lee, 2021).

Research analyzing and proposing improvements for digital talent development policies has often used hierarchical analysis to measure policy priorities. Studies aiming to achieve the goal of cultivating excellent science and technology personnel analyzed the alignment and importance of talent development policies through perception surveys and AHP (Analytic Hierarchy Process), presenting evaluation factors for designing and operating science and technology talent development policies, and measuring priorities among these factors (Kim et al., 2011). Research deriving policy directions for fostering creative SW talent utilized the AHP research model, classifying the current status and issues of domestic SW talent development through macro-environmental analysis PEST and business strategy analysis SWOT, and ultimately deriving relative priorities among the classified policies through hierarchical analysis (Lee & Lim, 2013).

Existing research related to digital talent development has often focused on specific fields or proposed policies from a comprehensive macro perspective. However, due to the era of digital transformation across industries, the need for digital talent development is not limited to any specific technological field. To achieve the concrete goal of developing one million talents, it is necessary to propose methods and directions for talent development on a micro level. Based on the macro premise of digital talent development, we have outlined detailed directions by categorizing current government-implemented digital talent development policies at the project level.

2.2 Current Status of Digital Talent Development Support Policy Projects

Multiple identities refer to an individual's capacity to express different versions of the self either simultaneously or sequentially, depending on the context or environment. Wearing (2011) conceptualized this phenomenon as a psychological and social resource that enables individuals to perform various roles and explore distinct aspects of their identity across diverse social situations. In digital environments such as the metaverse—where physical constraints are absent—these identity expressions become significantly more fluid and unconstrained (Donath, 1999; Turkle, 1995).

The government plans to establish a sustainable talent development ecosystem through public-private collaboration to train a total of one million digital talents from 2022 to 2026. The MSIT aims to expand the number of SW-centered universities from 44 to 100, support graduate schools for advanced talent development in digital fields, operate the 'SW Academy,' and expand credit-linked internships. The MOE is strengthening SW and AI specialized curricula and digital competency at various educational levels. Additionally, the MOEL is building infrastructure for basic digital job skills, the MSS is operating the 'Year Dream School' for AI talent development and employment linkage, and the MOTIE is running a program to enhance digital transformation skills for corporate leaders.

The government's comprehensive digital talent development plan is divided into two main directions: training one million digital talents and transforming the digital education system. Firstly, it aims to timely nurture talents with the necessary skills to enhance national competitiveness and digital adaptability. Secondly, it seeks to transition to a digital-based education system aligned with technological advancements to provide a fair educational environment. The government has laid the foundation for ICT talent development through AI and SW education expansion policies, with the MSIT and the MOE each pursuing digital professional talent development policies. Specifically, the MSIT supports the development of science and ICT talents based on relevant laws, and this study categorizes digital talent development policies based on the support projects of IITP.

IITP implements various digital talent development policy projects, including formal education, field training, and overseas linkage support. Among these, there are eight projects targeting ICT universities and graduate schools, focusing on training master's and doctoral level advanced talents through the establishment of metaverse graduate schools and support for AI graduate programs. Additionally, IITP operates internship programs that strengthen practical skills through school-company linked education, emphasizing field-based practical abilities over theory-centric advanced talent development.

Beyond formal education and school-company linked education, IITP also offers non-degree education support to cover a broader range of participants. The Innovation Academy provides a two-year non-degree program for high school graduates and above, involving online tests and a one-month intensive course, followed by training for 750 selected candidates. This program combines self-directed SW education with corporate collaboration projects. Furthermore, the SW Maestro short- and long-term education support program offers expert mentoring to high school, university students, and graduates to nurture global SW talents. The digital talent development support projects implemented by IITP are used as foundational data for creating a hierarchical classification table to measure the priority among digital talent development policy projects.

3. Method

3.1 Analytic Hierarchy Process(AHP)

In this study, we utilized the Analytic Hierarchy Process (AHP) to analyze the priorities among digital workforce development policy projects currently being promoted by the government. As previously mentioned, the decision-making process of policies involves diverse opinions based on various interests, and the methods of workforce development are also subdivided according to their purposes and needs. However, considering the constraints due to limited budgets and organizational resources in government-supported projects, as well as the time lag in policy implementation and effect creation, it is necessary to prioritize various support policy projects and select the policies that should be intensively pursued for efficient support. Particularly, to address the absolute shortage of digital workforce in the domestic market, along with the qualitative mismatch between supply and demand, it is essential to reflect the opinions of various stakeholders. However, qualitative opinion gathering alone has limitations in persuading each interest, thus it is necessary to prepare decision-making data based on objective data derived from quantitative measurements. The AHP is one of the methodologies that addresses complex decision-making problems through mathematical analysis (Kim & Eo, 1994). It objectively evaluates various alternatives by considering multiple evaluation criteria of diverse attributes (Min & Kim, 2016), and measures the relative superiority between factors using the pairwise comparison method without directly evaluating absolute importance (Jang, 2009; Saaty, 1999).

The scope of digital specialists was set to include traditional ICT personnel and SW planning and development personnel, as well as those in new industries such as data science, blockchain, and metaverse. To measure the priorities of digital workforce development policy initiatives, a hierarchical classification of the current policy schemes was first implemented. The hierarchical classification was conducted by first collecting existing literature dealing with digital workforce development policy schemes, followed by investigating and classifying policies currently operated by the government and public institutions. Finally, referring to the standards of existing literature, a brainstorming session among researchers was conducted to complete a hierarchical classification table with 3 major group (A) and 9 subgroup (B) as shown in <Table 1>.

Based on the digital workforce development policies examined earlier and the current status of digital workforce development support projects by IITP, the hierarchical major group of digital workforce development policy initiatives were divided into three group in total. The first is the cultivation of advanced digital specialists, the second is the training of talents who can effectively use digital technology in their respective fields, and the last is the enhancement of digital skills and understanding at a cultural level in daily life. Based on this, the current status of digital workforce development support projects by IITP, which is the main implementing agency of digital workforce development policy projects, shows that support projects are categorized into three major groups in line with the three goals of the government's comprehensive plan for digital talent development. The first is support for regular education for cultivating advanced digital specialists, the second is support for school-enterprise linked education to train talents who can effectively use digital technology in their jobs, and the third is support for non-regular education to promote the enhancement of universal digital skills and understanding for a larger audience. Therefore, the hierarchical classification of digital workforce development policy initiatives in this study follows the major groups of IITP's digital workforce development support projects that well reflect the main goals of the government's digital talent development-related policies.

Within the three major groups, each was divided into three subgroups, creating a total of nine subgroups (B). Fundamentally, each support project under the three major groups (A) was found to be operated by distinguishing between projects for fostering junior-level experts (university students) and those for cultivating advanced specialists (master's and doctoral students). Therefore, under the subgroups (B) for each major category (A), two common classifications were established: support projects for training a large number of junior-level experts (university students) and support projects for training advanced specialists (master's and doctoral students). In addition, items not included in the aforementioned subgroups among the support projects currently conducted by IITP were categorized and additionally set under the subgroups (B).

Beyond the two aforementioned subgroups, a subgroup for supporting advanced workforce training through laboratory-level support was added in the regular education support projects. This includes projects aiming to cultivate core research personnel at the master's and doctoral level to drive national innovation growth through support for cutting-edge research projects in promising ICT technology fields with the purpose of research support, such as the University ICT Research Center Project. In school and enterprise linked education support projects, a subgroup for internship support linked with academic credits was established, as opposed to project-based support projects. In the case of non-regular education support, a subgroup for short-term course support targeting employees was established. By setting three subcategories (B) for each major group (A) in this manner, the hierarchical classification of digital workforce development policy initiatives was conducted, and based on this, a pairwise comparison survey was conducted targeting experts.

Table 1. *Measurement Variables*

Group(A)	Subgroup(B)	Key Content
Regular Education Support	Support for University Programs to Train a Large Number of Entry/Mid-Level Professionals (Bachelor's)	Focus on selecting and supporting universities specializing in digital education such as SW and AI to train a large number of entry/mid-level professionals (Bachelor's)
	Support for Establishing/ Operating Graduate Programs to Train a Small Number of Advanced Professionals (Master's/Ph.D.)	Select graduate schools specializing in digital education such as SW and AI to train advanced professionals (Master's/Ph.D.)
	Support for Training Advanced Personnel (Master's/Ph.D.) through Laboratory-Level Support	Select excellent research laboratories within graduate schools and support labor costs, practice/research funds to train advanced personnel (Master's/Ph.D.)
School + Company Linked Education Support	Support for University Student Credit-Linked Internships	Support internship programs linking credits for IT-related major students (university) with domestic and international companies to train professionals through practical experience
	Support for University Student (Mentee) + Corporate Practitioner (Mentor) Team Project Execution	Connect university students (mentees), academic advisors, and corporate practitioners (mentors) to support team project execution, fostering workforce development based on practical experience
	Support for Graduate (Master's/Ph.D.) + Corporate Joint Project Execution	Support the planning and execution of joint projects between graduates (Master's/Ph.D.) and companies, fostering workforce development based on practical experience
Non-Regular Education Support	Support for Training a Small Number of Highly Advanced Professionals	Select a small number of outstanding IT major university students through in-depth evaluation and provide intensive management to support the training of a small number of highly advanced professionals
	Support for Training a Large Number of Entry/Mid-Level Professionals	Select existing training institutions as training providers to support the training of a larger number of entry/mid-level professionals
	Support for Short-Term Education Programs for Employees	Support short-term education programs centered on employees in specialized fields at existing educational institutions, associations, etc.

3.2 Analysis Method

The survey was conducted as part of a policy study by The Federation of Korean Information Industry(FKII), with the aim of comparing and synthesizing the opinions of the demand and supply sources of digital specialists. The respondents were selected from SW .ICT company employees and university professors specializing in SW.ICT-related fields. To measure the relative priorities among policies using AHP, the survey was designed in a pairwise comparison format. It was conducted over 25 days from September 6 to September 30, 2021, by sending and retrieving emails. To reduce the decline in response consistency due to online data collection, a 5-point scale was used (Song & Lee, 2013), and responses with a Consistency Ratio (CR) of 0.2 or higher were excluded. Ultimately, data from 47 company employees and 19 university professors were collected, totaling 66 responses for analysis. The analysis was carried out using six methods with Excel 2016 and 'Cloud Social Science Research Automation.' First, based on the data from 66 respondents, the relative importance among the three major policy categories, the relative importance among the nine subcategories, and the relative importance of composite weights reflecting the major category weights in the subcategory weights were calculated. Subsequently, the samples from companies and educational institutions were separated to conduct a comparative analysis of major categories, subcategories, and composite weights by each group. Lastly, to explore alternatives for policy direction based on the quantitative analysis results, in-depth face-to-face interviews were conducted with four survey respondents.

4. Research Results

4.1 Relative importance of policy support

In the analysis of the relative importance among the three major groups (A) of digital workforce development support policy options, the 'Education Support Policy through School and Enterprise Linkage' emerged as the most important with a score of 0.470. This was followed by 'Regular Education Support' with an importance score of 0.305, and 'Non-Regular Education Support' with the lowest score of 0.225.

Regarding the relative importance analysis among the subgroups within each of the three major groups, in the 'Regular Education Support' category, support for the 'Training a Large Number of Junior-Level Personnel' through the selection of key universities was the highest at 0.419, while 'Laboratory Unit Training Support' was the lowest at 0.281. In the 'School & Enterprise Linked Education Support' category, support for 'Graduate and Enterprise Joint Projects' showed the highest importance at 0.396, and support for 'Undergraduate Credit-Linked Internships' had the lowest importance at 0.248. Lastly, among the three subgroups of 'Non-Regular Education Support,' support for 'Training a Large Number of Junior-Level Personnel' through existing private educational institutions was the highest at 0.382, although 'Short-Term Employee Training' support was similarly high at 0.374, while 'Training a Small Number of Top-Level Personnel' was the lowest at 0.244.

Table 2. *Relative importance and composite weighting of policy support measures*

Group(A)			Subgroup(B)			Global(A*B)	
Factors	weight	Rank	Factors	weight	Rank	weight	Rank
Regular Education Support	.305	2	University Programs to Train a Large Number of Entry/Mid-Level Professionals	.419	1	.128	3
			Establishing/Operating Graduate Programs to Train a Small Number of Advanced Professionals	.300	2	.092	5
			Training Advanced Personnel (Master's/Ph.D.) through Laboratory-Level Support	.281	3	.086	7
School + Company Linked Education Support	.470	1	University Student Credit-Linked Internships	.248	3	.117	4
			University Student (Mentee) + Corporate Practitioner (Mentor) Team Project Execution	.356	2	.167	2
			Graduate (Master's/Ph.D.) + Corporate Joint Project Execution	.396	1	.186	1
Non-Regular Education Support	.225	3	Training a Small Number of Highly Advanced Professionals	.244	3	.055	9
			Training a Large Number of Entry/Mid-Level Professionals Short-Term Education Programs for Employees	.382	1	.086	6
			Short-Term Education Programs for Employees	.374	2	.084	8

By applying the major groups weights to the subgroups weights to calculate composite weights, the analysis of the relative importance among the total 12 subgroups showed that 'Support for Undergraduate & Practitioner Linked Projects' had the highest importance at 0.186. This was followed by 'Undergraduate & Practitioner Linked Projects' at 0.167, and 'Training a Large Number of Junior-Level (Bachelor's) Personnel' at 0.128, with 'Support for Training a Small Number of Top-Level Personnel' at the lowest at 0.055.

To summarize the priority analysis of digital workforce development support policies, 'School & Enterprise Linked Education Support' was identified as the most prioritized policy direction among the major groups. In the detailed subgroups, educational program support through school and enterprise linkages, such as 'Graduate & Enterprise Joint Projects' and 'Undergraduate & Practitioner Linked Projects,' showed the highest importance.

4.2 Comparison of relative importance by group

A comparative analysis was conducted to identify the differences between educational institutions, which are the suppliers in terms of workforce development, and companies, which are the demanders, regarding policy support measures. In the major groups (A), educational institutions placed the highest importance on 'Regular Education Support' (.476), whereas companies prioritized 'School & Company Linked Education

Support' (.510). 'Non-regular Education Support' was rated the lowest in importance by both groups.

Table 3. *Relative importance and composite weight by group*

Factors	Edu.		Ind.		Gap
	weight	Rank	weight	Rank	
University Programs to Train a Large Number of Entry/Mid-Level Professionals	.134	4	.119	4	.016
Establishing/Operating Graduate Programs to Train a Small Number of Advanced Professionals	.178	2	.066	7	.112
Training Advanced Personnel (Master's/Ph.D.) through Laboratory-Level Support	.164	3	.062	8	.102
University Student Credit-Linked Internships	.069	6	.137	3	.068
University Student (Mentee) + Corporate Practitioner (Mentor) Team Project Execution	.105	5	.193	1	.088
Graduate (Master's/Ph.D.) + Corporate Joint Project Execution	.179	1	.181	2	.002
Training a Small Number of Highly Advanced Professionals	.067	7	.048	9	.020
Training a Large Number of Entry/Mid-Level Professionals	.056	8	.096	6	.039
Short-Term Education Programs for Employees	.047	9	.100	5	.052

Among the three subgroups (B) of 'Regular Education Support,' educational institutions prioritized 'Training of a Small Number of Advanced Personnel' (.374) and 'Support for Training at the Laboratory Level' (.344), while companies placed the highest importance on 'Training of a Large Number of Entry-Level and Mid-Level Personnel' (.480). In the 'School & Company Linked Education Support' category, educational institutions emphasized 'Graduate School & Company Joint Projects' (.506), whereas companies focused on 'Undergraduate & Practitioner Linked Projects' (.378) and 'Graduate School & Company Joint Projects' (.354). In the 'Non-regular Education Support' category, educational institutions showed a high importance for 'Training of a Small Number of Highly Advanced Personnel' (.394), while companies prioritized 'Short-term Education Support for Employed Personnel' (.410) and 'Training of a Large Number of Entry-Level and Mid-Level Personnel' (.394). The analysis of differences in policy support measures for digital workforce development revealed that almost all categories showed distinct priorities between the groups.

In the comparison of composite weights between the groups, educational institutions showed the highest weights for 'Graduate School & Company Joint Projects' (.179) and 'Training of a Small Number of Advanced Personnel' (.178). For companies, 'Undergraduate & Practitioner Linked Projects' (.193) and 'Graduate School & Company Joint Projects' (.181) were the most important. The category with the lowest importance was 'Short-term Education Support for Employed Personnel' (.047) for educational institutions, and 'Training of a Small Number of Highly Advanced Personnel' (.020) for companies. The largest gap in composite weights between the groups was observed in the 'Training of a Small Number of Advanced Personnel' (.112), while the smallest gap was in 'Graduate School & Company Joint Projects' (.002).

To summarize the group comparison results, educational institutions focus on regular education for training a small number of advanced personnel, whereas companies emphasize practical education for training a large number of entry-level and mid-level personnel, showing contrasting perspectives between the groups. The almost universal difference in priority across groups could lead to a mismatch in workforce supply and demand, which is noteworthy. Notably, the importance gap regarding regular education for training a small number of advanced personnel is .112, indicating the largest difference in opinion. However, both groups place high importance on 'Graduate School & Company Joint Projects' in the field of school & company linked education support, which deserves attention.

5. Conclusion

This study aims to measure the priority among various support programs in digital workforce development policy, suggest policy directions, and propose implications for establishing effective policies by reflecting the balanced opinions of demanders (industry) and suppliers (educational institutions). A survey was conducted with a total of 66 professionals and university professors in the digital field to evaluate the priority of policy programs. The results showed that education methods linked to schools and companies were the most preferred, and joint projects related to problem-solving in practical settings were highly valued.

In the group comparison, educational institutions showed a strong preference for training advanced personnel at the graduate level, while companies emphasized the importance of company-linked education at the undergraduate level. However, both sides assigned high importance to joint projects at the graduate level. These results indicate that practical, work-linked approaches should be prioritized in digital workforce development, confirming the high preference for work-linked education among companies.

The study emphasizes the necessity of practical, work-linked education and suggests that institutional support is needed to encourage corporate participation. To ensure the sustainability of company-linked workforce development projects, it is necessary to expand support or provide compensation to participating companies and to focus on supporting joint projects between advanced graduate-level personnel and businesses. This will help reduce opinion differences between educational institutions and companies and contribute to training talent that can be immediately applied to practical work.

The issue of digital workforce supply is identified as a significant problem due to not only qualitative mismatches but also quantitative shortages. To achieve the workforce development goals set by the government's comprehensive digital talent development plan, it is necessary to stabilize quantitative supply, requiring institutional support such as expanding the capacity of educational institutions. Since these supports involve sensitive interests, coordination at the government level is required.

Canada's co-op program is a successful example of practical, work-linked education, providing students with work experience through collaboration between companies and universities, where companies receive partial salary support for trainees and can hire excellent talent. Although similar programs are implemented domestically, more effective corporate support is needed by addressing issues such as limitations on participation duration and frequency and inefficiencies in talent recruitment linkage.

Unlike previous studies on digital workforce development, this study compares ongoing specific policy programs by type and suggests effective policy directions. However, the lack of reflection of trainees' opinions and insufficient detailed direction of the programs are pointed out as limitations. Future research is expected to present specific implementation plans for each technical field and workforce development method, contributing to the establishment and implementation of digital workforce development policies.

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References

Kim, K., Lee, K., & Kim, J. (2011). A Study on Policy Compatability and Priority on Science and Technology Human Development Policy. *Korean Comparative Government Review*, *15*(3), 201–226.

Kim, M. (2018). A Study on Priority Determination of Policy Evaluation Criteria for Sports IT Specialist -Focusing on Policy Analysis Stage in Policy Process-. *The Journal Of Humanities and Social Sciences 21*, *9*(3), 1259–1273.

Kim, S., & Uh, J. (1994). Priority Aggregation for AHP based on Experts Opinions. *Journal of the Korean Operations Research and Management Science Society*, *19*(3), 41–51.

Roh, K., & Yang, C. (2002). A Study on the Policy of the technical manpower of Small and medium SW companies in the Digital Convergence. *Journal of the Korea Convergence Society*, *13*(1), 89–99.

Min, J., & Kim, W. (2016). A Non Face-to-Face Private Loan Screening Model Employing the Ratings Approach of AHP:Development and Validation. *Journal of the Korean Operations Research and Management Science Society, 33*(3), 65–87.

Bae, D. (2001). Software Engineering Education for IT Industry in the 21th Century. *Journal of Computing Science and Engineering, 19*(12)*,* 12–20.

Song, K., & Lee, Y. (2013). Re-scaling for Improving the Consistency of the AHP Method. *Journal of Social Sciences*, *29*(2), 271–288.

Song, J., Lee, J., Seo, Y., & Kim, H. (2021). A Study on the Development policy of AI and SW Talent in the Fourth Industrial Revolution. Software Policy & Research

Institute. Retrieved from https://spri.kr/posts/view/23272?code=data_all&study_type=research

An, I., & Choi, S. (2015). A Study on the Human Resource Development of Digital Content. *Kroean Journal of Communication Studies*, *23*(3), 57–92.

Yoon, B., Lee, J., & Son, M. (2022). *Analysis and Implications of SW Competency Framework.* Software Policy & Research Institute. Retrieved from https://www.spri.kr/posts/view/23445?code=data_all

Lee, S. (2017). Digital Transformation Society and New Administration's Industrial Policy Direction. *Journal of Communication Research, 54*(4), 35–66.

Lee, J., & Lim, M. (2013). Derivation of Creative SW HRD Policy Using Analytic Hierarchy Process. *Journal of Digital Convergence, 11*(10), 95–102.

Jang, T. (2009). A Methodological Review of Using AHP and Conjoint Analysis for Measuring 'Importance'. *Journal of Practical Research in Advertising and Public Relations*, *2*(1), 7–20.

Jeon, W. (2016). Study on the Current Status of the Software Industry and Human Resource Development Plans. *Review of Korean Society for Internet Information*, *17*(2), 53-58.

Choi, S. (2003). Study on the Training of Digital Cultural Content Experts: Focusing on Graduate School Courses. The Journal of Cultural Policy, 15, 2–29.

Hwang, U., & Yoo, H. (2023). What Happened to the Software Industry During the Pandemic. *Journal of the Korea society of Information Technology Applications*, *28*(3), 109–125.

Ministry of Trade, Industry and Energy. (2022). *Results of the Survey on the Supply and Demand of Industrial Technology Personnel.* Institute of Information & Communications Technology Planning & Evaluation. Retrieved from https://www.iitp.kr/kr/1/knowledge/statisticsView.it?masterCode=publication&searClassCode=K_STAT_01&identifier=02-008-230126-000002

Alphabeta. (2021). *Unlocking APAC's digital potential: Changing digital skill needs and policy approaches*. Amazon Web Services. Retrieved from https://pages.awscloud.com/APAC-public-DL-APAC-Digital-Skills-Research-2021-learn.html

Satty, T. (1990). How to make a decision: the analytic hierarchy process. *Euro pean Journal of Operational Research*, *48,* 9-26

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