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Decomposition analysis of influencing factors of GPU-centric supercomputing demand: LMDI-based approach

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Abstract: With the introduction of AI technology, the supercomputing industry is transitioning from CPU-centric to GPU-centric, and many countries are making efforts to build new GPU-centric resources. The purpose of this paper is to discover new factors in demand management for efficient construction and operation of future national supercomputing GPU resources. Reflecting industry characteristics, we decompose the factors affecting existing CPU use into intensity effect, structure effect, and production effect indicators targeting CPU-only resources and GPU-only resources, and compare and analyze the influence of each factor. To estimate the influence of each factor, the Logarithmic Mean Divisia Index methodology was used, and annual CPU usage data from the Republic of Korea's national supercomputing center was used. As a result of the analysis, it was confirmed that CPU resources show a similar trend every year, and that the effects of the intensity and production indicators are continuously increasing. In the case of GPU resources, all indicators had an influence in the direction of increasing demand, and it was confirmed that the information/communication field was overwhelmingly showing the greatest effect.
Keywords: *CPU, Demand management, GPU, LMDI, Supercomputer.*

1. Introduction

Experts predict that the global GPU market will grow more than 20 times from $56.55 billion in 2023 to 1,414.39 billion in 2034. Looking at the GPU market share as of 2023, Asia Pacific was the largest at 32%, followed by North America at 27% and Europe at 23% [1]. The Asia Pacific region is predicted to rise very rapidly from USD 18.10 Billion in 2023 to USD 452.60 Billion in 2034. In the supercomputer industry, the demand for GPU resources is rapidly increasing compared to existing CPU resources due to the influx of large AI calculation demands. For supercomputers ranked within the top 10 in the Top 500 announced in 2024, the average proportion of GPU cores compared to the total number of cores rose to 79.6%. This is an increase of more than 30% compared to the 48.8% value in 2018. Additionally, based on the top 100 supercomputers, there were 71 CPU-centric supercomputers in 2018. However, by 2024, the number has decreased by more than half to 33, and more than 90% of the top 10 are GPU-centric supercomputers. In this way, the supercomputer industry is undergoing a paradigm shift from existing CPU-centered to GPU-centered [2].

Recently, the Korean government is building a joint utilization system based on supercomputer centers (specialized centers) in each field. Every year, the specialized center submits an operation plan for its resources and a plan for building new resources to the government. Now, considering the GPU market trend, the need to estimate GPU demand along with CPU has also emerged. Until now, specialized centers have estimated demand from existing users using the stated preference (SP) method. This is the most direct and quick way to calculate demand by asking expected users whether or not to use it. However, this method has limitations in that it investigates fragmentary and temporary opinions

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at a specific point in time. Therefore, to complement this, it is necessary to find factors affecting CPU and GPU demand based on many years of data, select factors that will have a long-term significant influence in the future, and confirm their influence. Therefore, this paper newly introduced the LMDI(Logarithmic Mean Divisia Index) methodology to decompose changes in the usage into various factors and interpret their influence with the purpose of increasing accuracy in estimating future GPU demand. Through this methodology, three factors - intensity effect, structure effect, and production effect - are discovered, and the existing four years of usage data are used to estimate the direction and size of each factor's influence and derive meaningful implications for demand management.

The structure of this paper is as follows. In Chapter 1, the introduction explains the background and necessity of the study, and in Chapter 2, the meaning of this study is presented through analysis of similar previous studies and major theories related to the study are explained. Chapter 3 explains the research method, data, and analysis results. Finally, Chapter 4 summarizes the results, explains the academic value of the study, and presents future usability and limitations.

2. Literature Review and Theoretical Background

Although the Divisia index methodology has not been introduced in supercomputing research so far, it is actively used in research on carbon dioxide emissions and energy consumption in many fields such as economy, transportation, and logistics. Li, et al. [3] reviews previous research on the LMDI method in the context of building carbon emissions to provide a comprehensive overview of its application. They also review the use of LMDI in the building sector, urban energy, and carbon emissions and discuss other methods such as the Generalized Divisia Index Method (GDIM), Decision Making Trial and Evaluation Laboratory (DEMATEL), and Analytical Structural Modeling (ISM) techniques. The advantages and disadvantages of these methods and their use in architecture are compared and contrasted with LMDI Li, et al. [3]. Wang and Zhen [4] investigates the drivers and development strategies of PV and wind energy development in China based on the LMDI model and elasticity analysis model [4]. In addition, Nyangchak [5] analyzes renewable energy efficiency and factors affecting it in Qinghai Province from 2000 to 2021. It uses a combination of logarithmic mean partitioned exponential factorization, data encompassing analysis of the Super-SBM model, and field studies using a rounded approach Nyangchak [5]. Kou, et al. [6] aimed to quantitatively decompose the historical evolution of annual operating expenses in Japanese public hospitals to identify the main drivers of the worsening imbalance between operating expenses and income over the past two decades Kou, et al. [6]. Igwe, et al. [7] presents an index decomposition analysis of carbon emissions in the transportation sector in Akwa Ibom State. The main objectives of the paper were to determine the energy consumption of the transportation sector, assess the economic growth of energy consumption in the transportation sector, and present the decoupling of carbon emissions from energy consumption using the LMDI decoupling method for the transportation sector [7].

Examples of research in which LMDI methodology was applied to new fields are as follows. Zhang, et al. [8] first uses social network analysis (SNA) methods to explore the nature of social network relationships between water use among provinces, builds a two-level model of SNA-LMDI, and decomposes the driving factors among provinces. Changes in water use in provinces Zhang, et al. [8]. Feng, et al. [9] scrutinized the evolution of water footprint from 2010 to 2020 using the water footprint theory and LMDI model, focusing on the archipelagic city of Zhoushan Feng, et al. [9]. Kou, et al. [6] aimed to quantitatively decompose the historical evolution of annual operating expenses in Japanese public hospitals to identify the main drivers of the worsening imbalance between operating expenses and income over the past two decades [6].

An example of prior research in a field similar to or partially related to supercomputers is the study of carbon dioxide emissions from cooling systems. Nizigiyimana and Chaiwiwatworakul [10] investigated the energy saving and CO_2 emission mitigation potential of the low-lift technology by which the chiller plant of high-temperature chilled water (15°C) is dedicated for the production process

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cooling, and the traditional chiller plant of the low-temperature chilled water is used to serve the building air-conditioning [10].

The results of previous research are summarized as follows. So far, the LMDI methodology has been mainly used in the energy and environment fields, and has been used to discover demand characteristics by decomposing it into various factors that affect energy consumption and carbon dioxide emissions and analyzing the effects of each factor. Recently, studies have been published that performed factor decomposition analysis by selecting various fields and new targets, and there are research cases applying the LMDI methodology in fields such as social networks, water resource usage, operating costs, and supercomputing cooling systems.

This paper attempted to apply the LMDI methodology to discover new key factors in demand management and derive implications in relation to the expansion of supercomputing GPU resources due to the increase in AI computational demand. A key feature different from existing studies is that it comprehensively analyzes the absolute size and relative weight of various factors affecting usage demand for existing CPU-centered resources and GPU-centered resources, taking into account the characteristics of the domestic industry.

Referring to the theoretical background of LMDI, it is one of the factor decomposition methodologies based on the Divisia index. Divisia index factor decomposition analysis is mainly used to microscopically analyze the characteristics of changes in consumption and emissions in the energy and environment fields. The Divisia index can decompose the change in energy consumption between two points in time, while the existing Laspeyres index analysis fixes factors other than the main factor at the base year. This can be divided into additive and multiplicative decomposition methods. The additive method is useful for determining the absolute size of a change in a specific variable, and the multiplicative method is useful for cases where there is a large deviation as it takes into account the rate of change. In this paper, LMDI factor decomposition analysis was performed. The LMDI analysis applied log-average weights in the existing Divisia index method, and its explanatory power was improved by solving the problem of the '0' value of the existing residual term and time series data. The LMDI analysis can be expressed mathematically as equation (1). Various factors affecting the analysis object C can be defined as $x_{n,i}$ quantitative variables. n refers to the number of factors, i refers to the field, industry, etc.

$$\mathrm{C} = \sum_i C_i = \sum_i x_{1,i}, x_{2,i} \cdots x_{n-1,i} x_{n,i} \quad (1)$$

In equation (1), the C values at two points in time can be defined as equations (2) and (3), the multiplicative structural formula is derived from equation (4), and the additive structural formula is derived from equation (5).

$$\mathrm{C}^0 = \sum_i x_{1,i}^0, x_{2,i}^0, \cdots\ x_{n-1,i}^0, x_{n,i}^0 \quad (2)$$

$$\mathrm{C}^T = \sum_i x_{1,i}^T, x_{2,i}^T, \cdots\ x_{n-1,i}^T, x_{n,i}^T \quad (3)$$

$$D_{tot} = \frac{C^T}{C^0} = D_{x1} D_{x2} D_{xn-1} D_{xn} \quad (4)$$

$$\Delta C_{tot} = C^T - C^0 = \Delta C_{x1} + \Delta C_{x2} + \cdots + \Delta C_{xn-1} + \Delta C_{xn} \quad (5)$$

The influence of the j th factor in equations (4) and (5) can be calculated through equations (6) and (7). Here, the influence of a factor is expressed as an index value that allows comparative measurement of quantitative changes by multiplying the log average value between two time points and the log change in the factor [9, 11, 12].

$$D_{tot} = \exp\{\textstyle\sum_i L\left(C_i^T, C_i^0\right) / L(C^T, C^0) \ln\left(x_{j,i}^T / x_{j,i}^0\right)\} \quad (6)$$

$$\Delta C_{tot} = \sum_i L(C_i^T, C_i^0) \ln\left(x_{j,i}^T / x_{j,i}^0\right) \quad (7)$$

$$\mathrm{L}(\mathrm{a}, \mathrm{b}) = (a - b)/(\ln a - \ln b) \quad (8)$$

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3. LMDI Analysis

We examined changes in supercomputing resource demand using the additive factorization method targeting CPU-centric resources and GPU-centric resources. Factors showing effectiveness were divided into three indicators: intensity effect (I_i), structural effect (S_i), and production effect (Q), referring to previous studies such as Ang [12]. This can be expressed mathematically as equation (9). U_i stands for Net CPU utilization by field, and W_i stands for Number of tasks by field. i refers to the application field in which supercomputer resources are utilized.

$$\mathrm{U} = \sum_i U_i = \sum_i (U_i/W_i)(W_i/W)W = \sum_i I_i S_i\, Q \quad (9)$$

Data for factor decomposition analysis was used from the National Supercomputing Center's Nurion and Neuron supercomputer operation data. As shown in Table 1, data such as the total number of daily tasks for each resource and CPU and system utilization rate by application field were processed and utilized for the period from 2020 to 2023, when GPU demand rose most rapidly.

Table 1.
Variable.

Variable	Definition	Unit
U_i	Net CPU/GPU utilization by field	%
W_i	Number of tasks by field	Ea
W	Total number of tasks	Ea
i	Industrial fields	Ea

In the case of Nurion, key data by application field is shown in Table 2. Through preliminary work, a total of 12 fields were selected by deleting 4 fields, including health and welfare, that did not show significant differences.

Table 2.
Data(Nurion).

Field	U_i				W_i			
	2000	**2021**	**2022**	**2023**	**2000**	**2021**	**2022**	**2023**
Materials	11.5	22.3	16	23.8	161	318	313	537
Physics	33.7	17.7	19.5	20.6	486	350	433	587
Chemistry	19.4	12.6	11.6	15.2	267	163	253	418
Mechanical	16.4	18.5	17.6	9.1	214	334	285	195
Earth science	7.1	6.9	11.2	7.2	114	95	206	152
Chemical engineering	5.7	8.4	7.8	6.7	83	93	133	152
Energy/Resources	1.4	4.1	3.9	6.1	19	60	73	119
Environment	0.4	1.4	1.2	3.4	6	16	26	78
Life science	1.8	3.9	1.4	3.3	27	66	65	157
Nuclear power	0.4	1.2	7.2	2.4	4	14	117	46
Electrical/Electronic	0.7	0.9	1.3	0.8	20	38	40	38
Construction/Transportation	0.6	0.9	0.6	0.8	7	11	10	15

In the case of Neuron, the main data by application field is shown in Table 3. Through preliminary work, a total of 10 fields were selected by deleting 4 fields, including nuclear energy, that did not show significant differences.

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Table 3.
Data(Neuron).

Field	U_i				W_i			
	2000	**2021**	**2022**	**2023**	**2000**	**2021**	**2022**	**2023**
Information/Communication	37.9	92.4	73.5	74.1	24	23	18	29
Chemistry	32.9	1.2	13.1	3.7	13	5	14	9
Electrical/Electronic	12.9	0.2	0.5	0.1	4	2	2	1
Materials	7.5	1.2	0.1	0.5	2	4	1	2
Life science	1.9	0.9	3.3	2	1	1	1	1
Physics	2	0.2	2.9	1.4	2	1	6	6
Chemical engineering	0.7	0.1	0.3	2.4	1	3	6	10
health care	0.1	1.9	1.6	0.8	1	1	1	1
Earth science	0.1	0.9	1	1.1	1	1	1	3
Mechanical	0.1	0.9	1.2	3	1	5	3	7

As a result of the additive analysis, if the value is a positive number, it means that the effect of this indicator worked in the direction of increasing CPU and GPU resource use, while a negative number means the opposite.

First, the analysis results of Nurion resources are shown in Table 4 and Figure 1. In the case of ΔI_i, the effect appeared in a negative direction in all fields, and the size in the Physics field (18.13) was the largest. On the other hand, ΔS_i shows both negative and positive effects in each field. Four fields, Physics, Chemistry, Mechanical, and Earth science, show a negative effect, and eight fields, including Materials, show a positive effect. The area that shows the greatest effect is Materials. $\Delta \mathrm{Q}$ has a positive effect in all fields, with the largest effect occurring in Physics, Chemistry, and Materials.

Table 4.
Decomposition analysis (Additive) results (2020~2023).

Field	ΔI_i**(INS)**	ΔS_i**(STR)**	**ΔQ(ACT)**	**Total**
Materials	-8.07	10.66	9.71	12.30
Physics	-18.13	-10.26	15.28	-13.10
Chemistry	-11.92	-2.17	9.88	-4.20
Mechanical	-6.15	-8.27	7.12	-7.30
Earth science	-1.96	-2.05	4.11	0.10
Chemical engineering	-2.74	0.19	3.55	1.00
Energy/Resources	-1.16	4.03	1.83	4.70
Environment	-0.60	2.79	0.80	3.00
Life science	-2.86	2.94	1.42	1.50
Nuclear power	-0.73	2.09	0.64	2.00
Electrical/Electronic	-0.38	0.05	0.43	0.10
Construction/Transportation	-0.33	0.13	0.40	0.20

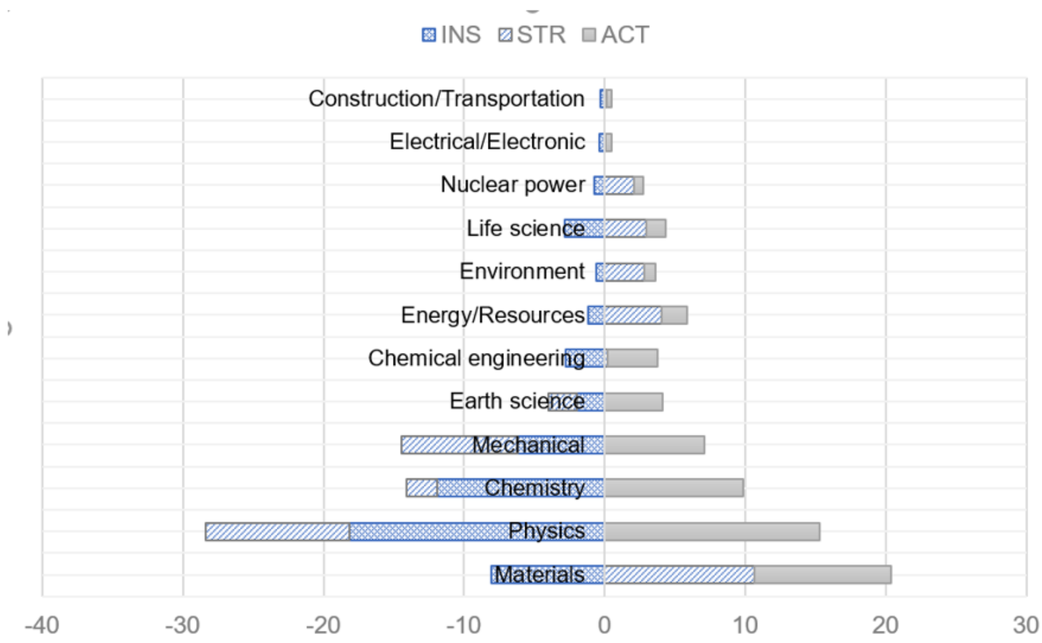

Figure 1.
Decomposition analysis (Additive) results (2020~2023).

The effects of annual indicators are shown in Table 5. The effect of ΔI_i in the negative direction gradually increased over time, and the effect in 2023 increased about 5.5 times compared to 2021. ΔS_i shows similar values every year at the level of 0.13 to 1.72, and ΔQ shows a gradual increase in the positive direction, showing the greatest effect at 55.17 in 2023. The combined effect of all indicators was of similar magnitude: -0.3 in 2021, 0.2 in 2022, and 0.3 in 2023.

Table 5.
Analysis results by indicator (by year).

	ΔI_i(INS)	ΔS_i(STR)	ΔQ(ACT)	Total
2021	-10.60	0.27	10.03	-0.30
2022	-32.97	1.72	31.45	0.20
2023	-55.01	0.13	55.17	0.30

Looking at Figure 2, it is shown that the size of the effects of ΔI_i and ΔQ increases every year.

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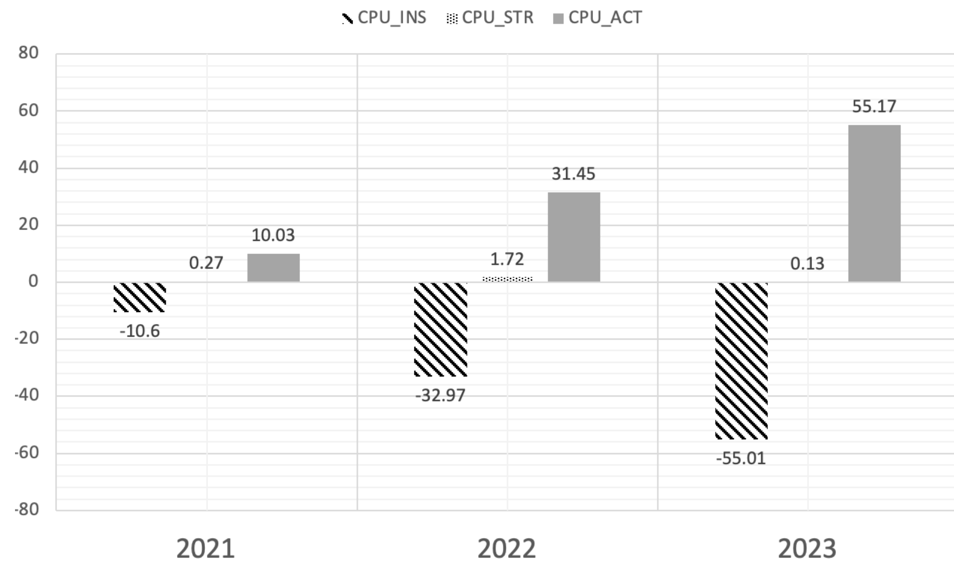

Figure 2.
Analysis results by indicator (by year).

Second, the analysis results targeting Neuron resources are shown in Table 6 and Figure 3. In the case of ΔI_i the average value for all fields was -1.92, with Information/Communication showing the highest value in the positive direction at 25.98, and Chemistry showing the lowest value in the negative direction at -24.29. ΔS_i shows positive effects in all cases except Information/Communication. Afterwards, the values increased in order of Materials 10.01 and Life science 9.69. ΔQ has a positive effect in all fields, with the largest effect occurring in Information/Communication, Chemistry, and Materials.

Table 6.
Decomposition analysis (additive) results (2020~2023).

Field	ΔI_i(INS)	ΔS_i(STR)	ΔQ(ACT)	Total
Information/Communication	25.98	-21.27	31.49	36.2
Chemistry	-24.29	1.82	7.79	-14.7
Electrical/Electronic	-9.15	0.76	1.54	-6.9
Materials	-7.00	10.01	1.51	4.5
Life science	-2.04	9.69	1.14	8.8
Physics	-4.47	7.37	0.98	3.9
Chemical engineering	0.18	6.86	0.80	7.8
health care	0.04	1.59	0.20	1.8
Earth science	0.19	1.61	0.24	2.0
Mechanical	1.37	3.17	0.50	5.0

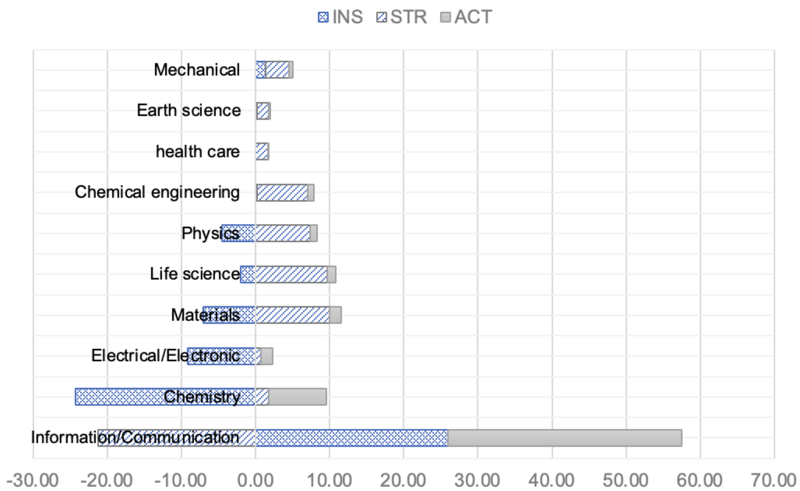

Figure 3.
Decomposition analysis (Additive) results (2020~2023).

The effects of the annual indicators are shown in Table 7. The effect of ΔI_i in the positive direction gradually increased over time, and the effect in 2023 increased about 7 times compared to 2021. ΔS_i decreased significantly from 12.04 in 2021 to a value of 1.8 in 2023. ΔQ appears to be at a similar level every year, with a deviation of ±5%. The sum of the effects of all indicators was 2.00 in 2021, 2.03 in 2022, and 2.03 in 2023.

Table 7.
Analysis results by indicator (by year).

	$\Delta \boldsymbol{I_i}$**(INS)**	$\Delta \boldsymbol{S_i}$**(STR)**	**ΔQ(ACT)**	**Total**
2021	13.40	21.35	9.54	44.29
2022	9.91	25.52	29.21	64.63
2023	-19.18	21.61	46.18	48.61

Looking at Figure 4, the effects of all indicators were positive until 2022, but the direction of the effect of ΔI_i changed for the first time in 2023.

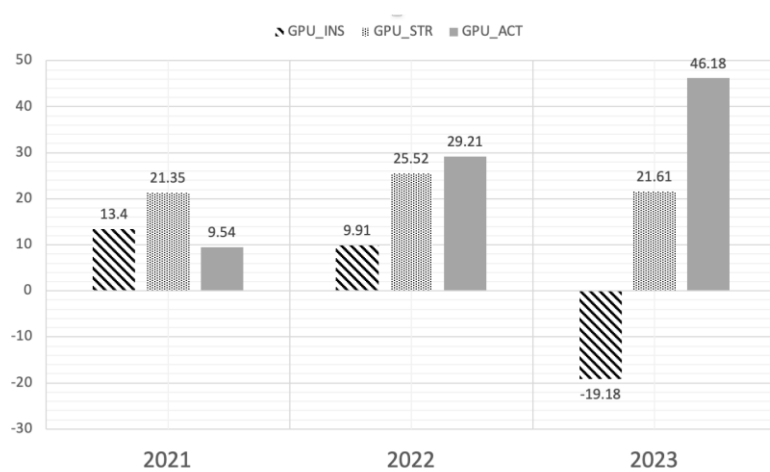

Figure 4.
Analysis results by indicator (by year).

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The results are summarized as follows. It was assumed that the trends in the analysis results would remain the same in the future. It is expected that the trend of CPU resource demand and use will be similar to the previous one. However, since the individual effects of the I_i and Q indicators appear large, it is necessary to monitor whether the balance of these effects is maintained. Meanwhile, the effect of increasing demand for GPU resources is expected to continue. In particular, because the effect of the Q indicator is rapidly increasing, it is believed that there is a very high probability that a direct increase in GPU demand will be seen in the future. To explain the characteristic part, in the case of CPU resources, the polarization of the effect of each indicator was greatest in the physics field. The negative effects of I_i and S_i were the largest, and the positive effects of Q were the largest. In the construction transportation and electrical/electronic fields, the effect of each indicator was relatively small and did not show any significant influence on CPU demand. Another characteristic of Q is that it all shows effects in a positive direction. Looking at the overall effect, it shows the same trend every year, and it was confirmed that the effect of each indicator gradually increases. In the case of GPU resources, the effect of each indicator was relatively greatest in the information and communication field. The values of all indicators were the highest. In some cases, the positive effect was more than 20 times that of other fields. In the fields of mechanical, earth science, and health care, the effect of each indicator was very small and did not show a significant impact. As with CPU resources, the effects of Q were all in a positive direction. The overall effect showed a similar trend, but in 2023, the effect of the I_i indicator was negative for the first time, necessitating new monitoring of this.

4. Conclusion and Implications

This paper analyzed by indicator the effect of the demand for existing supercomputing CPU resources being converted to GPU resources as the demand for AI calculations increases. The LMDI methodology, which was mainly used in the energy/environment field, was applied to the supercomputing demand management field for the first time, and the effects of intensity, structure, and production indicators on demand changes were estimated for national CPU and GPU supercomputing resources. As a result of the analysis, it was confirmed that in the case of CPU resources, the effects of indicators affecting demand over the past four years have shown a similar trend, and the effects of I_i and Q indicators are gradually expanding. All indicators showed that GPU resources had an influence in the direction of increasing demand, and the size of the effect was the largest in the information and communication field, requiring intensive construction and operation management of GPU resources to respond to future demand.

The limitations of the paper are as follows. In the case of national supercomputing resources, which are divided into CPU resources and GPU resources, a correlation exists considering the size and increase/decrease trend of the effect of the analysis results. Therefore, it is necessary to derive more practical research results by additionally considering the impact on actual demand movements in the future.

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Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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