The Studies on Occupational Structure — Numerical Analyses of Occupations and An Analysis of Occupational Mobility — Summary

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1. Background

Today, there are many problems that involve employment and occupations and which must be resolved. Despite the falling birthrate and aging population, young people still have difficulties in finding jobs. While elderly people are expected as a labor force, as the possibility of raising the age at which pensions are payable is being discussed, middle-aged and older people also have difficulties in finding jobs. However, there are many small and medium-sized enterprises that cannot acquire necessary human resources, and there are sectors plagued with chronic labor shortages. With the progress of economic globalization, Japan faces severe economic competition from emerging countries. The development of the Internet and other information networks and progress in distribution systems has resulted in borderless goods and services. Japanese workers are thus put into a position of effectively competing with all others in the world.

Under such circumstances, this report is based on the viewpoint that intensive analyses of the relationship between humans and occupations could provide basis for solving these various problems. If humans are appropriately linked to occupations that match them, individuals can demonstrate their capabilities and their companies or organizations can also improve their performance. When companies and organizations improve their performance, the entire country can also enhance its competitiveness to survive global competition. If the realities of individual occupations are ascertained to specify the relationship between occupations and humans, an increasing number of people may be interested in industries plagued with labor shortages and in SMEs failing to attract human resources, which may help resolve such shortages.

So far, human data have been objectively quantified through the development of methods for diagnosing occupational aptitudes and orientations, while occupational information has remained descriptive and each occupation has been described with letters and visualized. When the relationship between humans and occupations is considered, however, such descriptive information cannot be used as objective criteria for deciding whether any occupations are suitable for specific persons. In this respect, the U.S. Department of Labor (DOL) launched the O*NET project in the1990s to quantify various aspects of occupations, assess occupations with common standards, and objectivize and optimize the relationship between humans and occupations. The O*NET project was not necessarily the DOL's first effort to develop numerical data of occupations. Its earlier Dictionary of Occupational Titles (DOT) not only provided descriptions of occupations but also set such vocational aptitude measures as G (general learning ability), V (verbal aptitude), N (numerical aptitude), Q (clerical perception), S (spatial aptitude), P (form perception), K (motor coordination), F (finger dexterity) and M (manual dexterity). The DOL has collected and provided data for these measures. As worker functions required for each occupation, it also provided DPT (data, people, thing) level information for each occupation. In a manner to further develop the DOT effort, the O*NET project has comprehensively considered the mix of necessary numerical measures and designed a comprehensive system of necessary numerical criteria, promoting occupational information development (JILPT 2003).

Under the social division of functions, the government is responsible for specifying occupations that are now required and expected to enjoy future growth and clarifying such occupations and requirements for them in order to effectively use human resources and promote economic development. For individuals, as well, career choices are important. Finding occupations in which individuals can make the best of themselves is one of the top priorities over their lifetime. Individuals are now required to demonstrate their respective abilities through their occupations in the face of global competition to live a powerful occupational life. Regarding occupational information, which is to be positioned as important in this sense, this study attempted to take a step further to set and quantify multidimensional scales on occupations, as done by the U.S. DOL, with the aim of specifying the relationship between humans and occupations.

Today, occupational mobility occurs frequently. Even while remaining in a company or an organization, an employee may change from the present occupation to another. On such occupational mobility, there had been no wide-ranging objective data. This report also attempted to indicate the realities of occupational mobility based on data for more than 50,000 people.

In this way, this report attempted the development of multidimensional and numerical criteria on occupations and the analysis of occupational mobility, which had been required but had failed to be implemented.

2. Research Objectives

While descriptive information on each occupation had been developed, no attempt had been made to set multidimensional scales of occupations and systematically analyze objective occupational data.

This study attempted to analyze data for more than 20,000 people collected through a web-based job analysis system and examine various dimensions of occupations, specify inter-occupation relations by dimension and objectively examine the relationship between humans and occupations.

This study also attempted to analyze the realities of occupational mobility by more than 50,000 people data that had not been aggregated for collected through an earlier reported Web Survey on Certifications (JILPT 2010).

3. Key Points of Results -- contents of each chapter --

To obtain numerical data on occupational interests, work values, work environments, skills and knowledge, we analyzed 601 occupations for each of which data for 30 or more people were collected. We thus covered data for a total of 21,033 respondents. While the web survey has its peculiar limitations, we aggregated respondents' assessments of their respective occupations, and this is one of the grounds for the numerical data. These numerical data represent job details as the core of any occupation from the viewpoints of occupational interests, work values, work environments, skills and knowledge, providing standards for each occupation. Following are the key points of this study that analyzed and considered these numerical occupational data and job changes from various aspects. Numerical criteria for the 601 occupations are given in Appendix 1 of Chapter 7.

(1) As for occupational interests, six personality types based on a Holland study are widely used at home and abroad. The types are called RIASEC, covering Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. Through our study, numerical criteria of RIASEC for the 601 occupations have been made available. For the first time in the world including the United States, data have been collected from such a large number of workers on their own occupations (Chapter 2).

(2) Based on the U.S. DOL O*NET project, we set six types of work values—achievement, growth, social status, relationships, independence and working conditions—and collected data for these types, getting what could be described as numerical criteria for the six types of work values (Chapter 2).

(3) A factor analysis of 14 items for which data were collected on work environments provided five factors—sitting work, relations with others, outdoor work, influence and responsibility, and assembly-line work (Chapter 3).

(4) Regarding skills required for each occupation, we obtained two basic skill factors—fundamental and mathematical—based on 10 items subjected to the survey. As for cross-functional skills, we obtained four factors based on 25 survey items—technical, human, computer and goods management. Occupations with higher factors scores are generally appropriate (Chapter 4).

(5) As for knowledge required for each occupation, we obtained seven factors—science and technology, arts and human studies, medical care, business and administration, languages, civil engineering and security, and chemistry and biology—based on 33 items subjected to the survey (Chapter 4).

(6) A factor analysis based on the frequency of words found in task lists provided 27 factors—over-the-counter sales, research, consulting/support, diagnosis, surface processing, food manufacturing, cooking, design, passenger services, painting/cutting, education/guidance, cutting/shaping, checks and maintenance, nursing/assist, photographing, measuring/surveying, transportation, quality improvement, safety checks, news gathering and reporting, printing/bonding, painting/polishing, rearing/observation, checking the status, filming, order management, and systems. Occupations with higher scores on each factor are generally appropriate (Chapter 5). This indicates that the 27 factors can be assumed for the overall tasks and used for classifying occupations. For tasks that had been described while failing to be quantified for mutual comparison, we can now use 1 or 0 as numerical data indicating whether or not any specific the factor of tasks is included in each occupation.

(7) As for occupational mobility, we analyzed responses to a question about the present and previous occupations in the earlier reported Web Survey on Certifications (JILPT 2010). The responses had been left unanalyzed. A total of 581 occupations for each of which 30 or more people provided data were classified into three groups—occupations continued by respondents (continuation), occupations into which respondents flowed from previous occupations (inflow), and occupations from which respondents flowed into present occupations (outflow), covering a total of 51,146 respondents. We

acquired objective data indicating what occupations people continue frequently, from what occupations people flow into certain occupations, and into what occupations people flow out from certain occupations (Chapter 6).

(8) We established numerical criteria on 30 aspects for each occupation -- skills (six factors), knowledge (seven factors), work environments (five factors), occupational interests (six items) and work values (six items), getting. Correlations between the 30 aspects indicated some interesting features of occupations such as, for example, the association between occupational interests and work values (Chapter 7).

(9) The appendix indicates numerical criteria for 601 occupations based on the 30 aspects. The data are standard scores against 0.0 for an average and 1.0 for a standard deviation, allowing the comparison between data for these occupations to find numerical relations between occupations and each occupation's relative position among all occupations (Chapter 7).

(10) Numerical criteria for occupations can be used to determine the distances between specific occupations. For job changers who usually look for occupations similar to their respective present occupations, the numerical criteria can serve as objective data indicating what occupations are closer to each other (Chapter 7).

As mentioned above, both human information, including occupational aptitudes and orientations, and occupational information are required for finding and changing jobs and vocational trainings, and they have been used for matching job offers and job search requests. However, no scale or numerical criteria had been made available for occupational information. This study has developed numerical criteria for occupational interests, work values, work environments, skills and knowledge for each occupation and transformed descriptive task lists into numerical data. Regarding occupational mobility, we objectively sorted out data for occupations for continuation, those for inflow and those for outflow. The numerical criteria can be viewed as one of the fundamental information for analyzing job-finding, job changes and vocational trainings.

4. This Study's Significance: Multidimensional Scaling of Occupations and New Information

The government is responsible for providing accurate information on growing occupations and labor shortage occupations in order to achieve optimal human resources placement and promote economic efficiency and development. It is also important for individuals to choose occupations in which they may spend much time over their lifetime. Citizens have the right to assume occupations where they can demonstrate their abilities and make the best of themselves. Occupational information is required for finding such occupations, as well as for providing employment services. Occupational information is also the premise for vocational trainings because details of education and training depend on what skills and what education and training are required for each occupation, how occupations will change in the future and what skills are required when occupations transform.

Occupational information includes various matters (Figure 1). This study used a large-scale web survey to collect data on occupational interests, work values, skills, knowledge and work environments, which are the core of occupational information but had failed to be analyzed sufficiently because of their abstractness. We attempted to conduct a factor analysis of these data to specify their structure. Since occupational information generally includes education and training information, social and economic trends and job offers as listed in Figure 1, we excluded these factors and focused on occupational tasks, and their aspects concerning required abilities and orientations.

Various aptitude tests and diagnostic methods for interests have been developed to scale human abilities and orientations that are also abstractive concepts. This study has scaled abstractive parts of occupational information concerning required tasks, abilities and orientations.

Figure 1 Occupational Information and Other Various Information

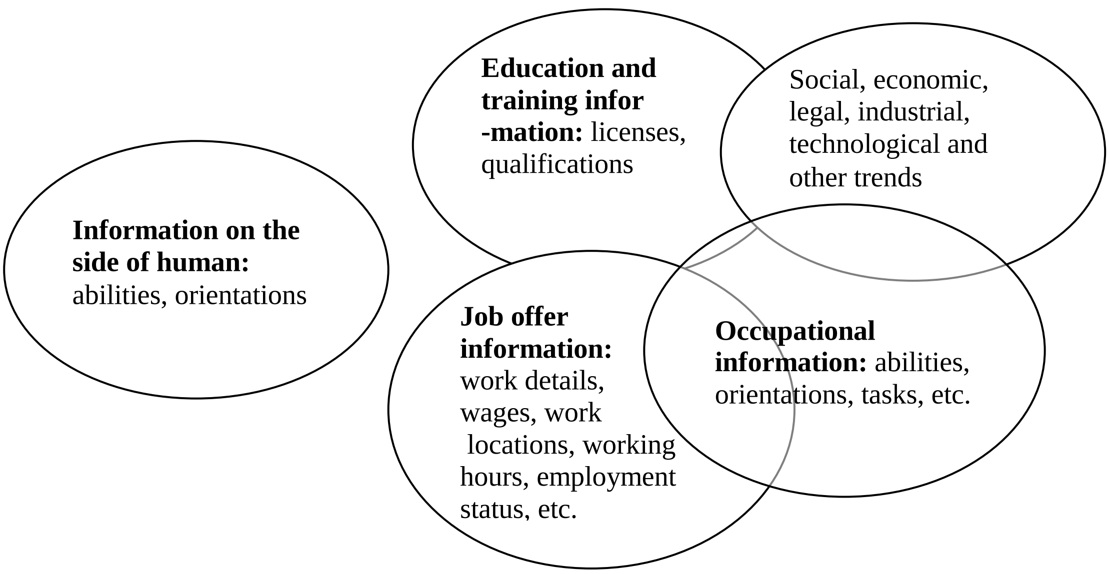
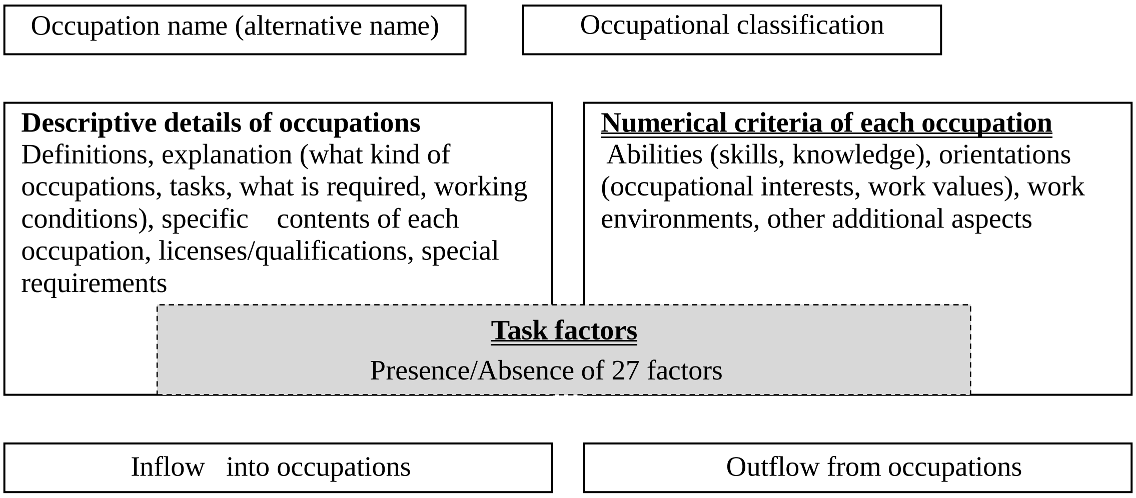


Figure 2 Components of Occupational Information



Occupational information can be indicated as in Figure 2. Of the information components, this study analyzed the underlined ones, specifying numerical criteria (multidimensional scaling), task factors and inflow into certain occupations and outflow from these occupations. There have been no occupational information items so far. Although tasks are descriptive information, we extracted 27 common factors from tasks, making it possible to consider occupations horizontally in line with the presence or absence of these common factors. Therefore, Figure 2 indicates task factors in a broken-line square as involving both the descriptive details of occupations and the numerical criteria of occupations. In this way, this study added new objective information based on survey data for numerical criteria of occupations (multidimensional scaling), task factors, inflow into occupations and outflow from occupations. The JILPT has collected and sorted out occupational information over a long term since it began to edit the Occupation Handbook, after the then Ministry of Labour had collected such information. Making a step forward from occupational information focusing on descriptions, this study set various common factors (dimensions and axes), developed numerical criteria for occupations on these dimensions and axes, and provided objective data including inflow into and outflow from occupations.

5. Numerical Criteria for Occupations and Their Analyses

(1) Occupational interests, work values, work environments, skills, knowledge

We analyzed numerical data about occupational interests, work values, work environments, skills and knowledge for 601 occupations for each of which 30 or more respondents provided information, covering a total of 21,033 respondents. The analyses of each item found the following points:

As for occupational interests, six personality types based on a Holland study are widely used at home and abroad. Through our study, numerical RIASEC criteria on the 601 occupations have been made available. The Holland theory assumes short or long distances between the six types. Interests close to each other in the RIASEC hexagon are assumed as similar, while those that are distant from each other, including those located diagonally, are assumed as far different. Occupations have also been roughly classified into the six types and assumed as having close or distant relations in the hexagon in the same manner. RIASEC data obtained for the 601 occupations met these assumptions (Chapter 2).

Based on the U.S. DOL O*NET project, we set six types of work values and collected data for these types, acquiring what could be described as numerical criteria for the six types of work values (Chapter 2).

A factor analysis of 14 items for which data were collected on work environments provided five factors—sitting work, relations with others, outdoor work, influence and responsibility, and assembly-line work. These factors meet research results of Strong et al. (1999), indicating an appropriate composition of factors. Numerical data based on the five factors can be said to be criteria for work environments (Chapter 3).

Regarding skills required for performing occupations, we acquired two basic skill factors—fundamental and mathematical. As for cross- functional skills, we acquired four factors—technical, human, computer and goods management. Occupations with higher factors scores are generally appropriate (Chapter 4). Skills required for occupations can be subdivided unlimitedly and can also be roughly divided into a small number of groups. In this study, we obtained two and four factors, or a total of six factors, based on responses from actual employees.

As for knowledge required for performing occupations, we acquired seven factors—science and technology, arts and human studies, medical care, business and administration, languages, civil engineering and security, and chemistry and biology—based on 33 items obtained from the survey. These factors basically meet past studies including Peterson et al. (1995), indicating an appropriate composition of factors (Chapter 4).

Numerical data on occupational interests, work values, work environments, skills and knowledge were collected from a total of 21,033 employees. While the web survey has its peculiar limitations, we aggregated respondents' assessments of their respective occupations. This is one of the grounds for the numerical criteria.

These numerical data represent occupation details as the core of occupational information from the viewpoints of occupational interests, work values, work environments, skills and knowledge, providing numerical criteria for each occupation. Numerical criteria for the 601 occupations are given in Appendix 1 of Chapter 7.

(2) Relations between numerical criteria

This study successfully scaled occupational interests, work values, work environments, skills and knowledge, obtaining numerical criteria for 601 occupations. What are the relations between the six data for occupational interests, the six data for work values, the five data for work environments, the six data for skills and the seven data for knowledge? Can we use the total of 30 aspects to depict profiles of occupations?

Table 1 and 2 indicate correlations between the 30 numerical criteria. While we can acquire a total of 30 x 30 correlation matrices, we here indicate correlation matrices for 18 aspects—six for skills, seven for knowledge and five for work environments—representing abilities (Table 1) and those for 17 aspects—six for occupational interests, six for work values and five for work environments—indicating orientations (Table 2). Work environments can be viewed as indicating abilities if considerations are given to what environments are required for specific occupations. They can also be interpreted as representing orientations if considerations are given to what work environments are favored. Therefore, work environment data are put into both correlation matrices for abilities and orientations.

The correlation matrices are based on numerical criteria for 601 occupations and we can find various interesting relations based on the criteria. Regarding abilities, for example, fundamental skills requiring overall cognitive functions show higher scores for medical professionals, lawyers and so on (Chapter 4), and have relatively high correlations with mathematical skills, human skills, medical care, languages, relationships with others, and influence and responsibility (in the tables, correlations measuring .500 or more are gray). Mathematical skills show higher scores for researchers and so on (Chapter 4), and have relatively high correlations with fundamental skills, computer skills, science and technology, and so on. Regarding interests, R (realistic) shows higher scores for occupations dealing with specific things (Chapter 2). Although R has no high correlation at .500 or more in Table 2, it has a high negative correlation with S (social) and a high positive correlation with assembly-line work, as indicated by higher absolute correlation coefficients. This means that occupations dealing with things have negative interests in human relations and focus on assembly-line work. I (investigative) shows higher scores for researchers and scholars and has high correlations with advancement, social status and independence in work values. People in investigative occupations can feel advancement, have high social status and work independently. The above shows part of the relations indicated by Table 1 and 2. Many other interesting relations between numerical criteria are seen as indicating occupational profiles.

(3) Multidimensional and numerical criteria of occupations and their potentials

Appendix 1 of Chapter 7 indicates all numerical criteria scaled from a total of 30 aspects for 601 occupations. From these occupations, four distinguishing ones were selected for Figure 3 and

4. All numerical criteria in Table 1 are standard scores against an average of 0.0 and a standard deviation of 1.0. Figure 3 and 4 also indicate standard scores against an average of 0.0 and a standard deviation of 1.0.

Regarding occupational interests in Figure 3, the advertisement designer has high A (artistic) and E (enterprising) scores, while the accounting clerk has a low achievement score but a high working conditions score. The four occupations show little difference in social status.

Regarding skills in Figure 4, the programmer has a high computer skill score. As for knowledge, the mold design engineer has a high score for science and technology. The advertisement designer has a high score for arts and human studies. Regarding work environments in Figure 4, the four occupations indicate similar trends including high scores for sitting work and lower scores for outdoor work.

In this way, the tables of numerical criteria for 601 occupations can transform characteristics of occupations into numerical data. A person who enters a new occupation may use the table to compare the old and new occupations and find how they are different or similar. Given that Appendix 1 of Chapter 7 gives scores against an average of 0.0 and a standard deviation (SD) of 1.0, the person can find the relative position of the new occupation among various occupations. This means that the person can know whether the importance of skills or knowledge is average (close to 0.0) and certain SDs away from the average. The probability of 2 SDs away from the average is limited to several percent, indicating that the relevant occupation is put into a distinguished position among many occupations. For example, Figure 3 shows that the advertisement designer’s A (artistic) score is more than 2 SDs away from the average, indicating a remarkable feature. Figure 4 indicates that the programmer’s computer score is nearly 3 SDs away from the average, mirroring a distinguished position.

As explained above, the table of numerical criteria allows us to compare between 601 occupations and find their relative positions.

Table 1 Correlations between Numerical Criteria for Skills, Knowledge and Work Environments (601 occupations, 21,033 respondents)

	Fundamental skills	Mathematical skills	Technical skills	Human skills	Computer skills	Goods management skills	Science and technology	Arts and human studies	Healthcare	Business and administration	Languages	Civil engineering and security	Chemistry and biology	Sitting work	Relations with others	Outdoor work	Influence and responsibility	Assembly-line work
Fundamental skills	1	.525 **	-.335 **	.813 **	.270 **	.115 **	.002	.369 **	.647 **	.268 **	.760 **	.155 **	-.011	.396 **	.684 **	-.358 **	.529 **	-.198 **
Mathematical skills	.525 **	1	.286 **	.293 **	.682 **	.258 **	.618 **	.041	.342 **	.046	.489 **	.284 **	.474 **	.250 **	.064	-.078	.142 **	.194 **
Technical skills	-.335 **	.286 **	1	-.306 **	.489 **	.332 **	.665 **	-.323 **	-.228 **	-.226 **	-.315 **	.187 **	.321 **	-.280 **	-.403 **	.287 **	-.106 **	.614 **
Human skills	.813 **	.293 **	-.306 **	1	.135 **	.112 **	-.135 **	.299 **	.717 **	.336 **	.617 **	.292 **	-.139 **	.132 **	.816 **	-.153 **	.507 **	-.258 **
Computer skills	.270 **	.682 **	.489 **	.135 **	1	.502 **	.828 **	.062	-.004	.319 **	.186 **	.293 **	.239 **	.245 **	-.009	-.078	.058	.334 **
Goods management skills	.115 **	.258 **	.332 **	.112 **	.502 **	1	.380 **	.232 **	.046	.467 **	-.145 **	.349 **	.380 **	-.183 **	-.013	.135 **	.168 **	-.009
Science and technology	.002	.618 **	.665 **	-.135 **	.828 **	.380 **	1	-.113 **	-.161 **	.002	.044	.299 **	.248 **	.156 **	-.237 **	.129 **	-.075	.468 **
Arts and human studies	.369 **	.041	-.323 **	.299 **	.062	.232 **	-.113 **	1	.333 **	.249 **	.311 **	.230 **	.073	.168 **	.261 **	-.061	.239 **	-.314 **
Healthcare	.647 **	.342 **	-.228 **	.717 **	-.004	.046	-.161 **	.333 **	1	.095 *	.579 **	.305 **	.112 **	.079	.536 **	-.120 **	.483 **	-.246 **
Business and administration	.268 **	.046	-.226 **	.336 **	.319 **	.467 **	.002	.249 **	.095 *	1	.128 **	.352 **	-.063	.106 **	.360 **	-.080	.203 **	-.204 **
Languages	.760 **	.489 **	-.315 **	.617 **	.186 **	-.145 **	.044	.311 **	.579 **	.128 **	1	.282 **	-.077	.544 **	.553 **	-.293 **	.344 **	-.083 *
Civil engineering and security	.155 **	.284 **	.187 **	.292 **	.293 **	.349 **	.299 **	.230 **	.305 **	.352 **	.282 **	1	.157 **	.029	.235 **	.425 **	.253 **	.118 **
Chemistry and biology	-.011	.474 **	.321 **	-.139 **	.239 **	.380 **	.248 **	.073	.112 **	-.063	-.077	.157 **	1	-.250 **	-.282 **	.174 **	-.049	.115 **
Sitting work	.396 **	.250 **	-.280 **	.132 **	.245 **	-.183 **	.156 **	.168 **	.079	.106 **	.544 **	.029	-.250 **	1	.192 **	-.382 **	.160 **	.109 **
Relations with others	.684 **	.064	-.403 **	.816 **	-.009	-.013	-.237 **	.261 **	.536 **	.360 **	.553 **	.235 **	-.282 **	.192 **	1	-.165 **	.588 **	-.195 **
Outdoor work	-.358 **	-.078	.287 **	-.153 **	-.078	.135 **	.129 **	-.061	-.120 **	-.080	-.293 **	.425 **	.174 **	-.382 **	-.165 **	1	-.054	.004
Influence and responsibility	.529 **	.142 **	-.106 **	.507 **	.058	.168 **	-.075	.239 **	.483 **	.203 **	.344 **	.253 **	-.049	.160 **	.588 **	-.054	1	.051
Assembly-line work	-.198 **	.194 **	.614 **	-.258 **	.334 **	-.009	.468 **	-.314 **	-.246 **	-.204 **	-.083 *	.118 **	.115 **	.109 **	-.195 **	.004	.051	1

Note 1) Correlation coefficients between aspects are calculated using scores of 601 occupations for each of which 30 or more respondents provided data. The base data cover 21,033 respondents.
Note 2) ** indicates results significant at the 1% level and * indicates results significant at the 5% level. Those for correlation coefficients at .500 or more are shaded.

Table 2 Correlations between Numerical Criteria for Occupational Interests, Work Values and Work Environments (601 occupations, 21,033 respondents)

	R (realistic)	I (investigative)	A (artistic)	S (social)	E (enterprising)	C (conventional)	Achievement	Growth	Social status	Relationships	Independence	Working conditions	Sitting work	Relations with others	Outdoor work	Influence and responsibility	Assembly-line work
R (realistic)	1	.235 **	-.016	-.436 **	-.268 **	-.080	.133 **	-.082 *	-.172 **	-.111 **	.036	-.216 **	-.243 **	-.295 **	.222 **	.014	.359 **
I (investigative)	.235 **	1	.215 **	-.081 *	.292 **	-.326 **	.423 **	.617 **	.585 **	-.072	.527 **	.212 **	.391 **	.057	-.247 **	.191 **	.079
A (artistic)	-.016	.215 **	1	.271 **	.437 **	-.482 **	.549 **	.501 **	.194 **	.372 **	.521 **	-.376 **	.149 **	.151 **	-.199 **	.190 **	-.250 **
S (social)	-.436 **	-.081 *	.271 **	1	.532 **	-.041	.286 **	.455 **	.364 **	.743 **	.327 **	.117 **	.016	.776 **	-.217 **	.399 **	-.506 **
E (enterprising)	-.268 **	.292 **	.437 **	.532 **	1	-.254 **	.408 **	.563 **	.449 **	.365 **	.508 **	.149 **	.363 **	.579 **	-.243 **	.255 **	-.260 **
C (conventional)	-0.08	-.326 **	-.482 **	-.041	-.254 **	1	-.474 **	-.469 **	-.156 **	-.150 **	-.491 **	.293 **	-.135 **	-.015	.043	-.026	.295 **
Achievement	.133 **	.423 **	.549 **	.286 **	.408 **	-.474 **	1	.764 **	.500 **	.464 **	.799 **	-.280 **	.118 **	.262 **	-.018	.482 **	-.263 **
Growth	-.082 *	.617 **	.501 **	.455 **	.563 **	-.469 **	.764 **	1	.742 **	.472 **	.747 **	.075	.340 **	.491 **	-.295 **	.455 **	-.265 **
Social status	-.172 **	.585 **	.194 **	.364 **	.449 **	-.156 **	.500 **	.742 **	1	.298 **	.537 **	.428 **	.408 **	.509 **	-.230 **	.531 **	-.052
Relationships	-.111 **	-.072	.372 **	.743 **	.365 **	-.150 **	.464 **	.472 **	.298 **	1	.407 **	-.093 *	-.213 **	.571 **	-.073	.398 **	-.444 **
Independence	.036	.527 **	.521 **	.327 **	.508 **	-.491 **	.799 **	.747 **	.537 **	.407 **	1	-.140 **	.238 **	.272 **	-.135 **	.449 **	-.349 **
Working conditions	-.216 **	.212 **	-.376 **	.117 **	.149 **	.293 **	-.280 **	.075	.428 **	-.093 *	-.140 **	1	.277 **	.284 **	-.308 **	-.010	.124 **
Sitting work	-.243 **	.391 **	.149 **	.016	.363 **	-.135 **	.118 **	.340 **	.408 **	-.213 **	.238 **	.277 **	1	.192 **	-.382 **	.160 **	.109 **
Relations with others	-.295 **	0.057	.151 **	.776 **	.579 **	-.015	.262 **	.491 **	.509 **	.571 **	.272 **	.284 **	.192 **	1	-.165 **	.588 **	-.195 **
Outdoor work	.222 **	-.247 **	-.199 **	-.217 **	-.243 **	.043	-.018	-.295 **	-.230 **	-.073	-.135 **	-.308 **	-.382 **	-.165 **	1	-.054	.004
Influence and responsibility	.014	.191 **	.190 **	.399 **	.255 **	-.026	.482 **	.455 **	.531 **	.398 **	.449 **	-.010	.160 **	.588 **	-.054	1	.051
Assembly-line work	.359 **	.079	-.250 **	-.506 **	-.260 **	.295 **	-.263 **	-.265 **	-.052	-.444 **	-.349 **	.124 **	.109 **	-.195 **	.004	.051	1

Note 1) Correlation coefficients between aspects are calculated using scores of 601 occupations for each of which 30 or more respondents provided data. The base data cover 21,033 respondents.
Note 2) ** indicates results significant at the 1% level and * indicates results significant at the 5% level. Those for correlation coefficients at .500 or more are shaded.

Figure 3 Numerical Profile Example (occupational interests, work values)

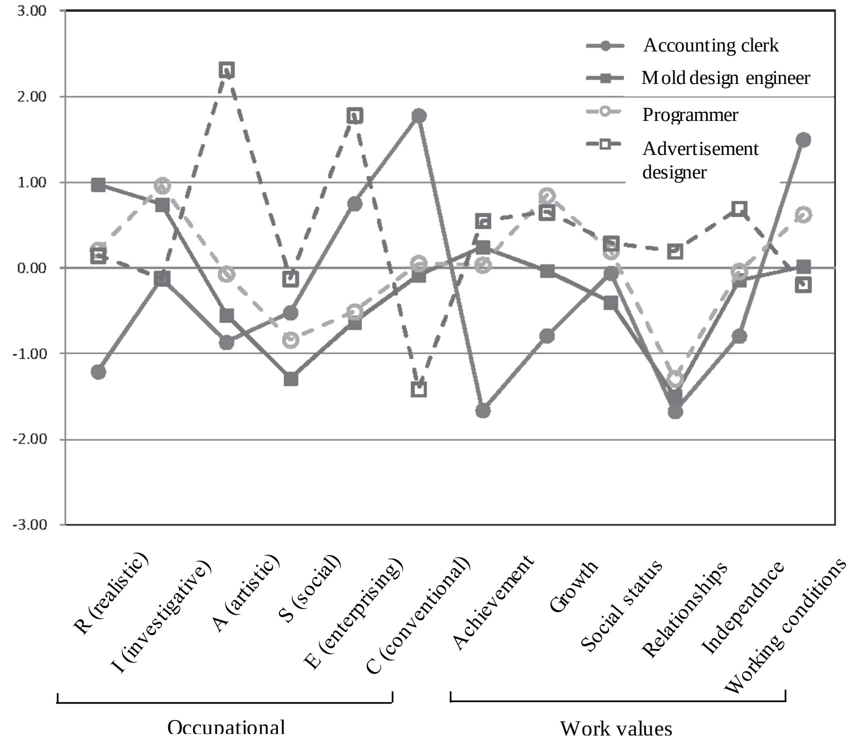
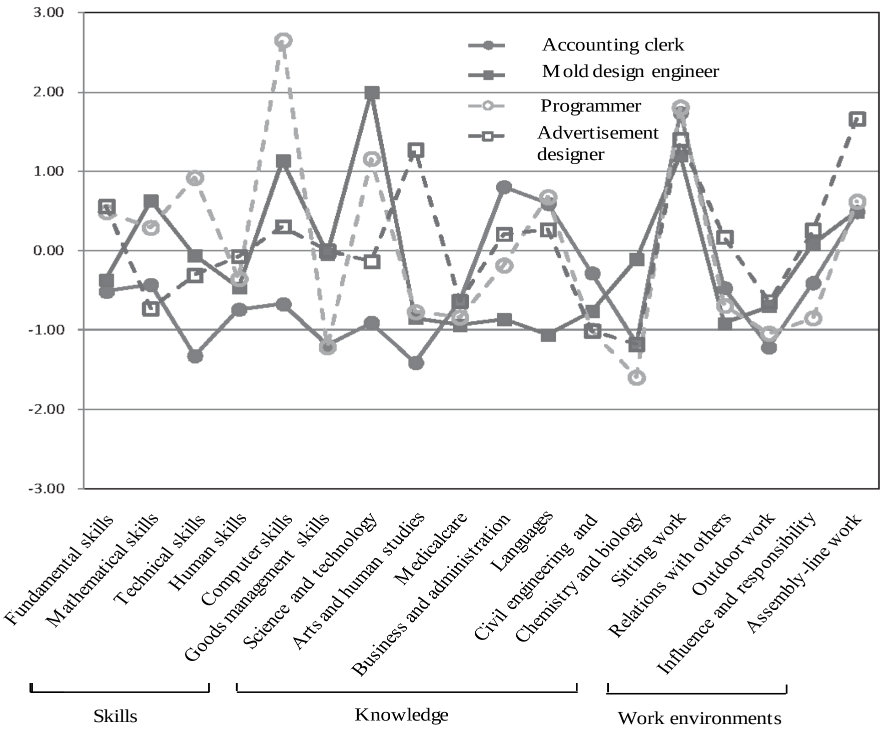


Figure 4 Numerical Profile Example (skills, knowledge, work environments)



(4) Quantifying of tasks: task factors

A factor analysis based on the frequency of words extracted from tasks provided 27 factors including over-the-counter sales etc. Occupations with higher factor scores are generally appropriate (Chapter 5). This indicates that the 27 factors can be assumed for tasks and be used for classifying occupations. Correlations between 450 occupations regarding the 27 factors, skills, knowledge and work environments indicate assumed appropriate relations (Chapter 5).

For tasks that had been described while failing to be quantified for mutual comparison, we can now use 1 or 0 as numerical data depending on whether the specific task factor is included in a occupation. This indicates that each occupation can be explained by 27 task factors. While occupational interests, work values, work environments, skills and knowledge have been successfully scaled to provide numerical criteria, the 27 task factors can indicate aspects that the numerical criteria cannot explain. A checklist, if it is developed,-may objectively confirm tasks of each occupation based on 27 task factors.

(5) Distances between occupations and their potentials

Appendix 2 of Chapter 7 indicates distances between occupations. Euclidean distances were computed from a total of 30 aspects in numerical criteria—six for skills, seven for knowledge, five for work environments, six for occupational interests and six for work values—as analyzed above. Among the distances, the shortest 10% are shaded. The data are all standard scores against an average of 0.0 and a standard deviation of 1.0 and used here as they are. Distances can be computed between all 601 occupations.

The inter-occupational distance matrix shows how short or far distances between occupations are as indicated by numerical criteria for skills, knowledge, work environments, occupational interests and work values. Table 3 indicates the first six occupations and those close to the six, based on Appendix 2 of Chapter 7. For the first two—the actuary and aroma therapist, no other occupation than they themselves is shaded, showing that the two occupations are far distant from any other occupations. Coming next is the clerk to which the accounting clerk, school clerk, administrative clerk (national), administrative clerk (prefectural or municipal), stationary retailer and so on are close. Close to the general machinery engineer are the semiconductor engineer, mold design engineer, electronics engineer, production and quality control engineer, mold maker and so on. Close to the rice farmer are the greenhouse vegetable farmer, fish farmer, formwork carpenter, plasterer, agricultural engineer and so on. The web creator is close to the advertisement designer, graphic designer, book editor, magazine editor, system engineer (software development) and so on. Table 3, though picking up only a small part of the appendix, indicates roughly appropriate relations between occupations.

People planning to change occupations may frequently seek those that are close to their present occupations. Based on occupation names, they decide whether specific occupations are close to or far away from their respective present ones. However, data like the appendix may allow people to list up occupations that are close to their present ones as indicated by the numerical criteria. As a matter of fact, only the table does not specify relations between occupations. If any special skill, license or qualification is required for an occupation indicated by the table as close to the present one, it may not be easy to switch to the occupation. While taking such possibility into account, people may use the table as one reference for finding occupations to which they may switch.

In this way, Appendix 2 can be viewed as an application of numerical criteria in Table 1. Using the numerical criteria, occupations can be compared from various aspects as shown in Figure 3 and 4, and a specific occupation's short or long distance from others can also be indicated as in Appendix 2 of Chapter 7.

Table 3 Distances between Occupations

		Actuary		Aromatherapist		Clerk		General machinery engineer		Raice farmer		Web creator
1	Actuary	0.000	Aromatherapist	0.000	Clerk	0.000	General machinery engineer	0.000	Rice farmer	0.000	Web creator	0.000
2	Product developer	4.882	Industrial counselor	5.405	Accounting clerk	2.617	Semiconductor engineer	2.630	Greenhouse vegetable farmer	2.887	Advertisement designer	2.709
3	International civil servant	4.992	Café owner	5.589	School clerk	3.210	Mold design engineer	2.678	Fish farmer	3.464	Graphic designer	3.239
4	Patent attorney	5.126	Cosmetics salesperson	5.634	Administrative clerk (national)	3.508	Electronics engineer	3.101	Formwork carpenter	4.121	Book editor	4.157
5	System engineer (application specialist)	5.187	Artist manager	5.870	Administrative clerk (prefectural or municipal)	3.989	Production and quality control engineer	3.338	Plasterer	4.393	Magazine editor	4.319
6	System engineer (information technology architect)	5.241	Life insurance salesperson	6.151	Stationery retailer	4.235	Mold maker	3.851	Agricultural engineer	4.468	System engineer (software development)	4.586
7	Administrative clerk (national)	5.257	Chinese dish cook	6.238	Purchasing clerk	4.268	Programmer	4.021	Stable attendant	4.865	Technical illustrator	4.680
8	System engineer (software development)	5.295	Social education director	6.246	Taxi dispatch operator	4.422	Personal computer assembler/adjuster	4.233	Woodworking machine operator	5.183	System engineer (application specialist)	4.693
9	Production and quality control engineer	5.298	Auto salesperson	6.379	Data input operator	4.468	Machine repairer	4.266	Dry cleaner	5.343	Product developer	4.739
10	Tax officer	5.694	Funeral director	6.570	Car park manager	4.583	Engineering technology researcher	4.439	Shipwright	5.641	System engineer (information technology specialist)	4.757
11	System engineer (information technology specialist)	5.794	Advertisement director	6.661	Computer maintenance engineer (information technology maintenance engineer)	4.610	Computer maintenance engineer (information technology maintenance engineer)	4.464	Dyer	5.649	Magazine journalist	4.817
12	Commercial firm official	5.809	Tour conductor	6.704	Product controller	4.626	Customer engineer	4.486	Building janitor	5.838	Customer engineer	4.863

Note) The eleven closest occupations for each of the first six occupations in Appendix 2 of Chapter 7 are given in the order of distance. As in Table 2, occupations with the 10% shortest distances from each of the six are shaded.

6. Analysis of Occupational Mobility

As for occupational mobility, we analyzed responses to a question about the present and previous occupations in the earlier reported license and qualification survey (JILPT 2010). The responses had been left unanalyzed. A total of 581 occupations for each of which 30 or more people provided data were classified into three groups—occupations continued by respondents (continuation), occupations into which respondents flowed from previous occupations (inflow), and occupations from which respondents flowed into present occupations (outflow), covering a total of 51,146 respondents.

Since the data used here were collected to add information on licenses/qualifications and occupational mobility to occupational information provided by the "Career Matrix", it was aimed to collect information evenly for the 725 occupations assumed initially for the Career Matrix (the target number of occupations changed from 725 to 723 in the middle of the survey, and the Career Matrix had made 512 occupations public). As this analysis reorganized the data based on the classification of occupations as revised by the Ministry of Health, Labour and Welfare (MHLW) in FY2011, some bias was seen. However, continuation, inflow and outflow for broad categories of occupations are summarized as major findings as follows:

Responses that did not specify previous or earlier occupations were considered as indicating "continuation." Among broad categories A (managerial occupations) to K (transportation, cleaning, packaging and other occupations) in the MHLW-edited classification of occupations (broad category A has been exempted from the analysis because this category covers only three occupations with collected data accounting for only 181 respondents or 0.4% of the total), the rate of continuation was 66.8% for broad category F (security occupations) and 53.8% for broad category B (professional and engineering occupations), exceeding 50%. On the other hand, the rate of continuation was as low as 30.9% for broad category K (transportation, cleaning, packaging and other occupations), 35.6% for broad category G (agriculture, forestry and fisheries occupations) and 36.4% for broad category E (services occupations). The rate of continuation for the entire data came to 47.2%.

Rates of continuation by attribute indicate that the rate is higher for occupations where men are dominant, those where university graduates are dominant and those where full-time employees are dominant.

From the viewpoint of "inflow" (Table 4), inflow was frequent within broad categories B (professional and engineering occupations) and C (clerical occupations). The rate for inflow stood at 50.4% for "B to B" and 45.6% for "C to C." However, the rate for inflow from broad category D (sales occupations) to broad category C (clerical occupations) was also high at 20.3%. As for broad category D (sales occupations), the rate for inflow was high at 33.8% for "D to D," but the rate for inflow from broad category C (clerical occupations) was also high at 26.9%. Regarding broad category E (services occupations), the rate for inflow from C (clerical occupations) to E stood at

26.7%, exceeding 20.2% for “E to E.” The rate for inflow from D (sales occupations) to E was also high at 20.2%. The rate for inflow within broad category F (security occupations) stood at 12.1%, slipping below 22.8% for “B (professional and engineering occupations) to F,” 17.6% for “D (sales occupations) to F” and 14.2% for “H (production process occupations) to F.” The rate for inflow within broad category G (agriculture, forestry and fisheries occupations) was limited to 2.9%, while the rates of inflow from various occupations were high, including 24.5% from B (professional and engineering occupations), 20.3% from C (clerical occupations), 18.1% from D (sales occupations) and 15.4% from H (production process occupations). The rate for inflow within broad category H (production process occupations) was high at 30.3%, followed by 22.7% for “B (professional and engineering occupations) to H.” The rate for inflow within broad category I (transportation and machinery operation occupations) was high at 20.4%, followed by 20.6% for “B (professional and engineering occupations) to I.” The rate for inflow within J (construction and mining occupations) was limited to 14.5% against 27.6% for “B (professional and engineering occupations) to J,” 14.2% for “H (production process occupations) to J,” and 14.0% for “D (sales occupations) to J.” Many also flowed into broad category K (transportation, cleaning, packaging and other occupations) from other categories. The rate for inflow within K was as low as 8.2% against 18.1% for “H (production process occupations) to K,” 17.7% for “D (sales occupations) to K,” 17.3% for “C (clerical occupations) to K,” 13.3% for “B (professional and engineering occupations) to K,” and 10.0% for “I (transportation and machinery operation occupations) to K.”

As for outflow, details are skipped here while being indicated in Table 5. Outflow from broad categories C (clerical occupations), D (sales occupations), E (services occupations) and I (transportation and machinery operation occupations) to other categories was frequent. Broad category G (agriculture, forestry and fisheries occupations) features unique points regarding inflow and outflow. Many people flowed into G from B (professional and engineering occupations), C (clerical occupations), D (sales occupations), H (production process occupations) and so on, while outflow from G (agriculture, forestry and fisheries occupations) was limited, failing to appear in Table 5.

Chapter 6 considered whether the relationship between occupational mobility and the similarity of new and old occupations meets the tabulation of similar occupations in the revised MHLW-edited classification of occupations. This chapter also describes continuation and characteristic job changes (inflow and outflow) indicating occupations from which many people enter into certain occupations and those into which many flow from certain occupations. The chapter thus provides effective information for job placement and recruitment.

Table 4 Numbers of People and Rates (%) for Flow between Broad Categories (Inflow)

Present occupations	←	Previous occupations	Number for inflow*2	Rate for inflow*3
B (9,666)*1	←	B	4,855	50.4
		C	1,882	19.5
C (2,932)	←	B	470	16.1
		C	1,335	45.6
		D	595	20.3
D (3,101)	←	B	461	14.9
		C	833	26.9
		D	1,047	33.8
E (3,000)	←	B	516	17.2
		C	800	26.7
		D	604	20.2
		E	665	22.2
F (289)	←	B	66	22.8
		D	51	17.6
G (547)	←	B	134	24.5
		C	111	20.3
		D	99	18.1
		H	84	15.4
H (4,617)	←	B	1,047	22.7
		C	688	14.9
		D	710	15.4
		H	1,398	30.3
I (804)	←	B	166	20.6
		C	118	14.7
		I	164	20.4
J (843)	←	B	233	27.6
		J	122	14.5
K (1,015)	←	C	176	17.3
		D	180	17.7
		H	184	18.1

Note) Among broad occupation categories for which the number for inflow is at 50 or more with the rate for inflow at 10% or more, categories for the top 30 rates for inflow were selected and listed in the category order. Inflow within a broad category is shaded.
*1: Total number of people who flowed into present occupations (inflow).
*2: Number of people for each broad category from which they flowed into present occupations.
*3: Percentage share for each broad category from which people flowed into present occupations. Inflow within a broad category is shaded.

Table 5 Numbers of People and Rates (%) for Flow between Broad Categories (Outflow)

Present occupations	→	Previous occupations	Number for outflow*2	Rate for outflow*3
B (8,140)*1	→	B	4,869	60.1
		H	1,047	12.9
C (6,094)	→	B	1,889	31.2
		C	1,335	22.0
		D	833	13.7
		E	800	13.2
		H	688	11.3
D (4,518)	→	B	1,002	22.2
		C	595	13.2
		D	1,047	23.2
		E	604	13.4
		H	710	15.8
E (2,289)	→	B	558	24.4
		D	330	14.4
		E	664	29.1
		H	293	12.8
F (267)	→	B	58	21.7
H (3,502)	→	B	919	26.3
		H	1,398	39.9
I (876)	→	B	130	15.0
		C	98	11.3
		H	145	16.7
		I	164	18.9
		K	101	11.6
J (621)	→	B	112	18.0
		H	165	26.6
		J	126	20.3
K (519)	→	B	102	19.7
		H	107	20.7
		K	83	16.1

Note) Among broad occupation categories for which the number for outflow is at 50 or more with the rate for outflow at 10% or more, categories for the top 30 rates for outflow were selected and listed in the category order. Outflow within a broad category is shaded.
*1: Total number of people who flowed into present occupations from previous occupations (outflow).
*2: Number of people for each broad category into which they flowed from previous occupations.
*3: Percentage share for each broad category into which people flowed from previous occupations. Outflow within a broad category is shaded.

7. Research Findings and Implications

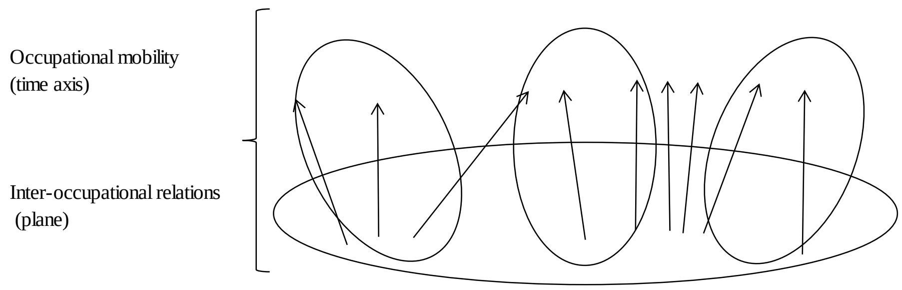
Occupations are a familiar concept for adults, and they have some ideas about their own occupation and the world peripheral thereto. Although stories about occupational experiences and personal impressions of occupations are abundant, people have little accurate knowledge about occupations that are not close to them. No systematic efforts had been made to objectively interpret, analyze or sort out multiple facets of occupations. Under such circumstances, this study has quantified occupations from various facets including abilities and orientations, and provided numerical criteria. This study's findings and implications are outlined as follows:

In Japan as well as in the United States, it has become difficult to conduct the collection of information about a wide range of occupations on an ongoing basis through the traditional occupational analyses, including visits to workplaces and interviews with workers. Regional occupational analysis field centers in the United States were all closed some 10 years ago. Occupational analyses by Japan's Ministry of Labor had been brisk only until the 1950s, and no nationwide analyses have been made since then. Under such circumstances, the web-based collection of information for this study is expected to become a new information collection method. Based on the web-based survey covering a total of 76,000 people, we collected information on detailed, cross-departmental numerical criteria and task-related data about 601 occupations and about the mobility between 581 occupations. As reviewed in this report, we used various methods to analyze and consider available data. Our study has appropriately depicted occupational profiles. Inter-occupational relations as indicated by data are roughly appropriate. In this way, the web-based collection of occupational information has been effective, indicating that this information collection method could be used for gathering other various information about a wider range of occupations. As noted in Chapter 1, however, web-based surveys fall short of grasping new occupations, occupations including unprecedented elements, unprecedented necessary requirements and so on. Traditional on-the-spot surveys−visits, interviews and analyses−are also necessary for covering such information. Traditional occupational analyses and information collection through web-based occupational analysis systems are complementary to each other.

Next, numerical criteria for 30 aspects—six for occupational interests, six for work values, five for work environments, six for skills and seven for knowledge—obtained in regard to each of the 601 occupations are criteria for each occupation. As indicated by Figure 4 and Table 3, these data can be used to depict inter-occupational relations. Each occupation can be plotted with a scale covering these factors, although such plotting is not illustrated here. As numerical criteria given in Appendix 1 of Chapter 7 are based on an average of 0.0 and a standard deviation of 1.0, each occupation's distance from the average can be obtained based thereon.

Furthermore, this study includes an analysis from a new dimension (or time axis) of occupational mobility. The time axis has been added to a two-dimensional analysis of numerical criteria for occupations, providing a new three-dimensional structure (Figure 5). Workers may change occupations over their lifetime. Even if they remain in the same companies or organizations without changing occupations, they may see their occupations details changing. The concept of adding the time axis to the occupational world can be viewed as better meeting realities. When seeking jobs, students may consider changes in job details over several years after their assumption of jobs. The objective understanding of the occupational world's three-dimensional structure including the time axis may provide people with information for making decisions when they seek jobs, change jobs or make career shifts.

Figure 5 Three-dimensional Occupation Structure including Time Axis



The 30 numerical criteria and occupational mobility information obtained through this study can be used in various ways and are expected to make contributions to various areas.

First, the numerical criteria may be used for enhancing the efficiency of matching between job offers and job search requests, which has so far been based only on job or occupation names. If job offer information is quantified under the 30 aspects and job seekers' abilities, orientations, careers and experiences are profiled under the 30 aspects, how and to what extent job offers meet or differ from job search requests may be visualized. When job seekers' vocational training is considered, their specific lacks or shortfalls regarding job offers may be used as a reference for selecting training courses. If vocational training courses are quantified under the 30 aspects in the future, the quantitative data may objectively indicate what training courses specific people should select. Job offers, job search requests and vocational training courses may be profiled under the 30 aspects, allowing for their comparison under the common criteria. Such comparison might have so far been made in relevant experts' heads based on their experiences. However, the 30 aspects of numerical criteria may be used for making decisions based on objective criteria. This may provide unprecedented matches between job offers and job search requests or unprecedented education and training choices. In this way, unprecedented solutions can be expected. The objective criteria will allow us to consider more accurate and creative matches between job offers, job search requests and training courses.

The second point, which may overlap partially with the first point, is that the numerical criteria may become common social criteria. Students and other job seekers may use the 30 aspects of numerical criteria for specifying their abilities, orientations and other personal characteristics in a multidimensional manner. They may make progress in their self-understanding that now consists only of vague images. Human resources experts at companies making job offers may also be able to quantify job offers' various facets including required abilities and orientations. While job offers usually describe job details, job descriptions have not been standardized, and, therefore, human resources experts make such descriptions based on precedents. In contrast, the numerical criteria may be used to specify the personal characteristics they seek.

The numerical criteria can be expected to become a framework for objective understanding of personal characteristics and job offers. If the numerical criteria are used more widely and new criteria are developed, they may be combined into common social criteria to profile individuals, occupations and education/training courses.

The third point is related to an ability development policy as a key part of national economic policies. Discussions on the policy must be based on information including specific industrial structure goals, and occupational categories and labor required for such goals. However such information is not sufficient yet. Then, the 30 aspects of numerical criteria may be used for quantifying new graduates' abilities and orientations and working people's experiences and careers (multidimensional quantification of the labor force structure), and the quantified data may be compared with requirements for a future industrial society, allowing for a numerical policy simulation.

Fourth, if web-based occupational analysis and other systems are used to collect and analyze various information, including occupational mobility (job change) data, in addition to the 30 aspects of numerical criteria, analysis results may provide basic occupation-wise career information for individuals who have various careers and consider their further career development. Such detailed objective information on occupations and careers is among the most desired information for career consulting. If public organizations accumulate information without depending only on consultants' guesses and experiences, they may be able to use the accumulated information for developing national criteria to support consultants.

Fifth, the numerical criteria can make academic contributions, including the provision of objective occupational information for developing new assessments and the quantification of personal careers for social surveys on occupations as attributes and for research on human resources management.

Specifying the occupational structure may lead to developing various assessments and checklists. Various diagnostic methods and checklists can be developed to measure required skills and knowledge, as well as occupational interests and work values, from the viewpoint of occupational requirements. Occupational interests mean personal interests that meet specific occupations. The 30 aspects of numerical criteria may also be used for developing the classification of occupations in the future. If the 30 aspects of numerical criteria are aggregated for occupations included into broad and middle categories for multiple classification drafts, a smaller dispersion within each broad or middle category and larger gaps among different broad or middle categories may be used as guidelines for an appropriate classification. This may allow us to use specific data for considering what classification draft is better than others. The 30 aspects of numerical criteria may also be used for other various future research and development projects.

Problem-solving measures under labor policy may include legislation and subsidies to guide society. Provision of information is also a leading measure to address policy challenges. The U.S. Department of Labor website ranks occupations subject to higher future growth and to present abundant job offers. This can be viewed as a way to effectively distribute labor for society while respecting personal independence. However, in this case, with only occupation names, it is impossible to understand what tasks are involved, what is required, or what types of persons are suitable for the occupation. This study has provided the numerical criteria of various occupational aspects, in addition to traditional descriptive information to indicate job details, requirements and suitable personal characteristics. As reviewed in Chapter 1, occupations as divisions of labor have existed since ancient days. The division of labor has helped improve technology and has triggered explosive production revolutions, leading to rapid industrial development. Information is required on occupations that exist as divisions of labor that serve as infrastructure to evolve and develop society. This study has made clear the occupation structure, which is core information, but that had been abstractive and difficult to understand.