Introduction to Quantitative Career Matching: How to Statistically Pick the Right Occupation

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Abstract

In this introductory paper, we address the crucial, but highly neglected, subject of data-driven career choice and development. We begin by sketching out the most basic approach to quantitative career matching, and test our model by calculating career compatibility coefficients with data from the United States' primary source of occupational information, the O*NET framework. We, then, illustrate the results with a sample of occupations from O*NET's database, and describe the best matches for each selected career. Despite the model's simplicity, we found career matches to be very accurate, although not as precise as they would be had we employed superior methods. In the future, we expect to cover some advanced material, deliberately left out of this introduction, and detail more sophisticated and performant models.

Keywords: Career matching; Career compatibility; Career choice; Career development; Vocational choice; Occupational Information Network.

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1 Introduction

Choosing the right occupation is one of the most important decisions in life. In fact, a considerable portion of a person's life – generally, a third of it – is actually spent working. Additionally, finding a career that is suitable for one's skill set and natural aptitudes greatly impacts job performance and overall satisfaction. Having sufficient compensation to feed a family, and adequate work-life balance, are also crucial. And, for some individuals, we could even cite self-fulfillment and ethical reasons as major factors contributing to the significance of work.

Given this overarching importance of career choice and development, we would expect to find many quantitative approaches to the issue in the scientific literature. Nonetheless, despite some competent efforts by psychometricians and personality theorists (e.g. Holland, 1959, 1997; Schein, 1978, 1993), not much has been done to address this problem in a purely data-driven manner.

In the late 1990s, however, a notable achievement in this area was brought about by the Occupational Information Network (National Center for O*NET Development [O*NET], 1998). Sponsored by the United States Department of Labor, this program set out to quantify job requirements in a standardized fashion. Their research resulted in a robust database of career paths, which includes numeric estimates of competence levels for dozens of abilities; as well as several other characteristics, such as the frequency of typical work activities, the seriousness of expected job hazards, etc. Their catalog of occupations is vast, and their data have been updated frequently for over two decades.

But even with such rich information publicly available, there is still a lack of statistical modeling of it. In this series of articles, we aim to fix this. Starting with the most immediate concepts, we expect to document all mathematical methods we have devised to tackle the study of career choice and development. Here, we detail a basic approach to quantitative career matching based on the estimation of compatibility scores. In the future, we shall cover more complex matching algorithms, and advanced topics, like identifying occupations' core attributes, assessing the generality of career paths (to distinguish between generalist and specialist workers), calculating employability coefficients, constructing optimal strategies for career planning, talent acquisition, and much more.

2 Methods

2.1 The Occupational Information Network

The Occupational Information Network (O*NET) is an American primary source of occupational information. It was developed during the mid 1990s, and published in 1998, by a team of public and private sector organizations, in partnership with the Department of Labor's Employment and Training Administration. Its aim is to facilitate the maintenance of a skilled workforce through the collection and dissemination of occupational data (Mariani, 1999; O*NET, 2024).

Essentially, the O*NET model provides a thorough, quantitative, description of hundreds of SOC (Standard Occupational Classification, see U.S. Bureau of Labor Statistics [BLS], 2018) career paths in a vectorized format. O*NET accomplishes this task by systematically evaluating the competencies of actual people in the labor market, on a 0 to 100 scale, in order to derive numeric guidelines on what attributes are required for each position.

Therefore, the resulting "career profiles" from O*NET's surveys are meant to be taken as "canonical representations" of SOC occupations: they "map out" what, say, an engineer, an accountant, or any other occupation tends to "look like", in terms of professional attributes.

2.2 Skill Sets

With the convenient structure of the O*NET framework in mind, we begin by defining and measuring the professional attributes that characterize each economic agent in the labor market. To do so, we establish a bounded, uniform scale from 0 (complete incompetence) to 100 (complete mastery), such that:

$$a_i^k \in [0, 100], \tag{1}$$

where a_i^k is the i-th professional attribute of a person k. Moreover, let us denote as a "skill set", or "career profile", the vector of their m attributes, like so:

$$\boldsymbol{a_k} = (a_1^k, ..., a_m^k). \tag{2}$$

Thus, all individuals in the economy – whether employed, or not – are mathematically described by their own skill sets, or career profiles; and this applies to regular SOC occupations as well, like the ones included in the O*NET database.

2.3 A Euclidean Approach to Career Matching

Finally, individuals and occupations are said to be similar to the exact degree to which their vectors of professional attributes, or skill sets, overlap.

To measure this compatibility, we can utilize several matching methods. Some of these are complicated, and require lengthy explanations, while others are much easier to introduce. As the scope of this article is very limited, we only cover the most basic of methods: the Euclidean approach to career matching.

2.3.1 An Initial Model for Euclidean Career Matching

In this approach to career matching, compatibility is estimated by the inverse function of Euclidean distance. Hence, we first define this concept:

$$d(\boldsymbol{a_k}, \boldsymbol{a_q}) = \|\boldsymbol{a_k} - \boldsymbol{a_q}\| = \sqrt{\sum_{i=1}^{m} (a_i^k - a_i^q)^2}. \tag{3}$$

Equation (3) measures the absolute distance from the professional attribute vector $\boldsymbol{a_k}$ to a comparison vector $\boldsymbol{a_q}$; in other words, it tells us how these two skill sets are *dissimilar*.

But, of course, our interest here is career compatibility, not its opposite. Furthermore, similarity is typically expressed as a percentage; and for this, we need dissimilarity to be bounded to a known interval. Therefore, in order to convert the Euclidean distance (3) to a similarity metric, we need to employ some sort of normalization procedure, like the following:

$$\tilde{d}(\boldsymbol{a_k}, \boldsymbol{a_q}) = \sqrt{\frac{\sum_{i=1}^{m} (a_i^k - a_i^q)^2}{\sum_{i=1}^{m} \max(100 - a_i^q, a_i^q)^2}}. \tag{4}$$

The denominator in equation (4) is the maximum theoretical distance to the $\boldsymbol{a_q}$ comparison skill set. That is, here we normalize distance (3) by calculating the distance to $\boldsymbol{a_q}$ from its most dissimilar vector. So, for each coordinate of the $\boldsymbol{a_q}$ skill set, we measure which distance would be greater: that from the scale's lower bound (viz. 0), or that from the upper bound (viz. 100), as any other distance has to be less than those to the scale's limits. This way, the denominator corresponds to the maximum distance to $\boldsymbol{a_q}$; and, consequently, the normalized distance $\tilde{d}(\boldsymbol{a_k}, \boldsymbol{a_q}) \in [0, 1] \ \forall \ \boldsymbol{a_k}, \boldsymbol{a_q}$.

At last, similarity is easily derived from the normalized dissimilarity:

$$s(\boldsymbol{a_k}, \boldsymbol{a_q}) = 1 - \tilde{d}(\boldsymbol{a_k}, \boldsymbol{a_q}). \tag{5}$$

As opposed to equations (3) and (4), this formula describes the measure to which career profiles are *similar*. Again, it is evident $s(\boldsymbol{a_k}, \boldsymbol{a_q}) \in [0, 1] \ \forall \ \boldsymbol{a_k}, \boldsymbol{a_q}$. Thus, we can estimate, as a percentage, how compatible a person is with an occupation, and whether they are alike in terms of their competencies, or not.

2.3.2 A Weighted Euclidean Approach to Career Matching

Although straightforward, the above method is far too simplistic, for each and every competency is given the same importance in matching; and this is, clearly, not reasonable. In reality, some professional attributes are, definitely, more important to some occupations, while to others they are less or even not important.

Consider, for instance, the absurdity of a barber who knows a lot about the arts, and fashion, and entertaining customers, and even accounting and bookkeeping, and yet does not know how to actually cut hair. One could call them artistic, or stylish, but hardly a barber. For despite the usefulness of all these other things for the barber, they are not nearly as important as their main activity (viz. cutting hair).

This is the issue of weighting professional competencies, and it is crucial for adequate career matching. In fact, to the degree to which attributes are said to be "central", or "indispensable", to certain career paths (like being able to cut hair is for a barber), so too weighting these attributes is indispensable for career matching algorithms to function properly.

Now, as it is with matching methods, here also we find a variety of manners of weighting professional attributes. The first, which we cover below, is to use linear weights. This said, quadratic, logistic, or any other sort of increasing weights can be employed as well. In our more complex career matching algorithms, for example, we make use of a specific weighting function to determine the "indispensability" of human capital (i.e. competencies' relative importance), and this vastly improves models' performance. For illustrative purposes, however, linear weights seem to suffice.

2.3.3 Linear Weights for Euclidean Career Matching

When implementing linear weights with the Euclidean approach, each distance between career profiles is multiplied by the attributes of the comparison skill set (viz. that to which compatibility is to be calculated). Thus, distances to the most important competencies are emphasized, while the remaining receive less importance.

Mathematically, the weighted metrics (with subscript w) for similarity scores and normalized distances are as follows:

$$s_w(\boldsymbol{a_k}, \boldsymbol{a_q}) = 1 - \tilde{d}_w(\boldsymbol{a_k}, \boldsymbol{a_q}), \tag{6}$$

where

$$\tilde{d}_w(\boldsymbol{a_k}, \boldsymbol{a_q}) = \sqrt{\frac{\sum_{i=1}^{m} a_i^q (a_i^k - a_i^q)^2}{\sum_{i=1}^{m} a_i^q \max(100 - a_i^q, a_i^q)^2}}. \tag{7}$$

With these adjusted equations, Euclidean distance is weighted proportionally to the professional attribute levels of the $\boldsymbol{a_q}$ career profile. This means that the matching algorithm optimizes itself for each comparison skill set, as irrelevant competencies are left out of the analysis, and the "indispensable" ones (e.g. cutting hair for a barber, dentistry for a dentist) are given their full importance.

2.3.4 Adjusting for Overqualification

A positive side effect of the use of weights in career matching is an implicit correction for the statistical penalties of overqualification. These arise, in the original approach, whenever an individual has additional competencies from other fields that are not required at a certain position, and cause the unadjusted distance (4) to yield less favorable similarity estimates. For, if $a_i^k > a_i^q$, then

$$\frac{\partial \tilde{d}(\boldsymbol{a_k}, \boldsymbol{a_q})}{\partial a_i^k} = \frac{\tilde{d}(\boldsymbol{a_k}, \boldsymbol{a_q}) \times (a_i^k - a_i^q)}{\sum_{i=1}^{m} (a_i^k - a_i^q)^2} > 0 \iff \frac{\partial s(\boldsymbol{a_k}, \boldsymbol{a_q})}{\partial a_i^k} < 0. \tag{8}$$

This overqualification problem is highly detrimental for matching accuracy, as it tends to "punish" people with many professional attributes, whether they are skilled generalists or merely hobbyists. But, of course, as the absurd scenario of the useless barber mentioned above, this too is not reasonable at all. Indeed, no one would say, for instance, that an airline pilot is less of a pilot if they also know how to cut hair, just as we do not say a barber is less of a barber if they cannot fly an airplane. Put another way, competencies that have "nothing to do" with an occupation should not be a limiting factor to career compatibility.

The application of matching weights helps to mitigate this, as the less important competencies are, rightly, given less importance; and those distances to completely irrelevant attributes (with competence levels of 0) are even nullified entirely, so that:

$$\tilde{d}_w(\boldsymbol{a_k}, \boldsymbol{a_q}) \leq \tilde{d}(\boldsymbol{a_k}, \boldsymbol{a_q}). \tag{9}$$

Therefore, if a person has additional, unnecessary, skills, these weighting techniques provide a correction for the penalties of overqualification, decreasing the normalized Euclidean distance and increasing compatibility.

2.4 Data

The version of the O*NET database utilized contains 873 unique career profiles, even including a few variants on top of SOC occupations. For brevity's sake, though, they are succinctly described below in terms of general clusters:

Table 1: General Occupational Statistics

Cluster	N[1]	Employment[2]	Wage[3]	Market Share[4]
Business Management & Administration	65	26,639,371	$59,924.00	21.05%
Health Science	99	16,856,404	$62,753.00	13.95%
Marketing	26	13,961,830	$45,512.00	8.38%
Manufacturing	138	13,644,785	$44,169.00	7.95%
Hospitality	42	17,416,290	$28,965.00	6.65%
Transportation, Distribution & Logistics	62	11,018,200	$45,511.00	6.61%
Architecture & Construction	86	9,005,327	$53,142.00	6.31%
Education & Training	64	7,266,480	$62,621.00	6.00%
Finance	22	5,255,514	$70,325.00	4.87%
Law, Public Safety, Corrections & Security	35	4,790,620	$61,985.00	3.92%
Information Technology	22	3,588,065	$82,061.00	3.88%
Human Services	38	7,823,620	$36,809.00	3.80%
Science, Technology, Engineering & Mathematics	70	2,207,815	$100,683.00	2.93%

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Table 1: General Occupational Statistics (Continued)

Cluster	N[1]	Employment[2]	Wage[3]	Market Share[4]
Agriculture, Food & Natural Resources	40	2,140,244	$51,134.00	1.44%
Arts, Audio/Video Technology & Communications	40	1,692,270	$57,836.00	1.29%
Government & Public Administration	24	1,166,588	$62,636.00	0.96%

[1] Number of SOC occupations plus variants.
[2] Total employment levels in the United States in 2022.
[3] Employment-weighted mean wages in the United States in 2022.
[4] Total cluster wages as a percentage of total wages in the United States in 2022.
Source: BLS, 2022; O*NET, 2023.

As it concerns matching procedures, career compatibility coefficients were estimated by comparing all available occupations to one another, instead of matching against human subjects. This was done for a few reasons: to ensure the model's internal consistency; to avoid potential sampling biases; because matching occupations to occupations is, essentially, the same as matching individuals to occupations (for both are defined by competency vectors); and, finally, because the O*NET data are, themselves, derived from rigorous labor market surveys, and consequently career profiles already are representative of the skills of real people. So, even though one of the model's end goals is to help *individuals* find the right career, at the present moment, we can test these methods "internally", without resourcing to further empirical research.

Unfortunately, this also means we cannot show most of our results, as the O*NET database contains too many career paths, and the scope of an introductory article does not allow for all their matches to be displayed. Hence, for this exercise, we only present four occupations: mechanical engineers, physicists, credit analysts, and dishwashers. These were choosen to illustrate a "sufficient range" of careers: two highly qualified STEM occupations, the first more "hands-on" than the latter; one of the simplest roles in the economy (viz. dishwashers); and the other somewhere in between (viz. credit analysts). Their main characteristics are summarized in Table 2.

Table 2: Summary of Sample Occupations

SOC	Occupation	Cluster	Employment[2]	Wage[3]
19-2012	Physicists	STEM[1]	18,840	$152,430.00
17-2141	Mechanical Engineers	STEM[1]	277,560	$95,300.00
13-2041	Credit Analysts	Finance	71,960	$77,440.00
35-9021	Dishwashers	Hospitality	431,840	$28,130.00

[1] "STEM" stands for "Science, Technology, Engineering, and Mathematics".
[2] Total employment levels in the United States in 2022.
[3] Median wages in the United States in 2022.
Source: BLS, 2022; O*NET, 2023.

The career profiles, or skill sets, used for matching were composed of three broad categories of professional attributes from the O*NET framework, namely: "Skills", "Abilities", and "Fields of Knowledge". These three categories combined sum to exactly 120 competencies, and are detailed in the Appendix. The remaining categories of attributes (e.g. "Interests", "Work Values") do not constitute "competencies" in the strict sense of the word, so they were not included in the analysis. Additionally, a few of the original attribute names were changed to reduce ambiguity (e.g. from "Design" to "Industrial Design").

3 Results

3.1 Most Compatible Occupations

Again, despite the small selection of four occupations, there are still too many career matches to be displayed here. Thus, we only illustrate the results of the weighted Euclidean approach with the ten most compatible occupations.

Table 3: Best Career Matches – Mechanical Engineers

Comparison Occupation	Similarity
Mechanical Engineers	1.00
Aerospace Engineers	0.90
Marine Engineers and Naval Architects	0.88
Nuclear Engineers	0.88
Mechatronics Engineers	0.87
Microsystems Engineers	0.86
Photonics Engineers	0.86

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Table 3: Best Career Matches – Mechanical Engineers (Continued)

Comparison Occupation	Similarity
Fuel Cell Engineers	0.86
Automotive Engineers	0.86
Materials Engineers	0.86
Mining and Geological Engineers, Including Mining Safety Engineers	0.86

Note: Similarity scores estimated with Euclidean matching and linear weights.
Source: Author's calculation based on O*NET, 2023.

Table 4: Best Career Matches – Physicists

Comparison Occupation	Similarity
Physicists	1.00
Astronomers	0.85
Mathematicians	0.80
Physics Teachers, Postsecondary	0.80
Materials Scientists	0.79
Engineering Teachers, Postsecondary	0.79
Nanosystems Engineers	0.78
Aerospace Engineers	0.77
Biochemists and Biophysicists	0.77
Nuclear Engineers	0.77
Computer and Information Research Scientists	0.77

Note: Similarity scores estimated with Euclidean matching and linear weights.
Source: Author's calculation based on O*NET, 2023.

Table 5: Best Career Matches – Credit Analysts

Comparison Occupation	Similarity
Credit Analysts	1.00
Accountants and Auditors	0.87
Loan Interviewers and Clerks	0.86

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Table 5: Best Career Matches – Credit Analysts (Continued)

Comparison Occupation	Similarity
Budget Analysts	0.85
Securities, Commodities, and Financial Services Sales Agents	0.85
Financial Examiners	0.85
Business Intelligence Analysts	0.85
Tax Preparers	0.85
Insurance Underwriters	0.84
Bookkeeping, Accounting, and Auditing Clerks	0.84
Tax Examiners and Collectors, and Revenue Agents	0.83

Note: Similarity scores estimated with Euclidean matching and linear weights.
Source: Author's calculation based on O*NET, 2023.

Table 6: Best Career Matches – Dishwashers

Comparison Occupation	Similarity
Dishwashers	1.00
Janitors and Cleaners, Except Maids and Housekeeping Cleaners	0.88
Maids and Housekeeping Cleaners	0.88
Pressers, Textile, Garment, and Related Materials	0.87
Models	0.87
Postal Service Mail Sorters, Processors, and Processing Machine Operators	0.87
Sewing Machine Operators	0.86
Laundry and Dry-Cleaning Workers	0.86
Orderlies	0.86
Cutters and Trimmers, Hand	0.86
Shoe and Leather Workers and Repairers	0.86

Note: Similarity scores estimated with Euclidean matching and linear weights.
Source: Author's calculation based on O*NET, 2023.

3.2 Similarity Matrix

We also found it useful to build a similarity matrix, with which one can easily compare occupations' compatibility coefficients:

Table 7: Similarity Matrix

	Mechanical Engineers	Physicists	Credit Analysts	Dishwashers
Mechanical Engineers	1.00	0.75	0.54	0.38
Physicists	0.80	1.00	0.57	0.34
Credit Analysts	0.75	0.66	1.00	0.54
Dishwashers	0.62	0.53	0.66	1.00

Note 1: Similarity scores estimated with Euclidean matching and linear weights.
Note 2: Comparison occupations on the horizontal axis.
Source: Author's calculation based on O*NET, 2023.

As noted in the similarity matrix, comparison occupations are on the horizontal axis, meaning that Table 7 should be read vertically. This is because the normalization (4) and weighting (7) techniques employed imply the characteristic symmetry of Euclidean distance is, in most cases, lost.

Therefore, the table shows, for example, that mechanical engineers have 62% compatibility with dishwashers, while dishwashers have only 38% compatibility with mechanical engineers; that is to say engineers are sufficiently qualified to perform the job activities of dishwashers, but not the other way around.

4 Discussion

Assessing the matching results in Tables 3–6, we could say this Euclidean model is quite accurate: mechanical engineers are matched to ten other types of engineers; while theoretical physicists are similar to astronomers, biophysicists, mathematicians, and scientific roles, in general; credit analysts, adequately, cluster with occupations in the financial industry; and dishwashers, in turn, have high compatibility with janitors, cleaners, and so-called "blue-collar" positions.

When we analyze Table 7, we find results to be likewise accurate. Firstly, the STEM career paths are fairly close to one another, at 80% similarity. This is expected, since engineers are, in a way, applied physicists. Dishwashers, on the other hand, are not really similar to either one, but are a little more compatible with credit analysts. And, finally, credit analysts, have roughly 60% similarity with the other three occupations, indicating they are somewhat compatible, and undifferentiated in this respect. It also stands out, as already mentioned, that the more "highly qualified" profiles have high compatibility scores with the "less qualified", or "simpler", ones, while the reverse is not true.

As regards precision, however, the Euclidean approach to career matching is evidently suboptimal. For one thing, similarity scores are too high, specially when comparing occupations that have little or nothing to do with one another, as we have in this exercise. That is, though the model's matching predictions "make sense", the degree of similarity, for some careers, is grossly overestimated.

Indeed, the compatibility of, say, dishwashers with engineers and physicists is relatively low, which is realistic; but, at almost 40%, it is still, objectively, not low enough. And the same applies to credit analysts, as well. For as an entry-level position in the field of Finance, credit analysts do seem to be some sort of "middle ground" between the other selected roles: in fact, their job activities are mostly mathematical in nature, yet are neither as demanding and abstract as those of physicists, nor as direct and concrete as the repetitive manual labor of dishwashers. So, in this sense, the estimated compatibility scores are correct. Nevertheless, the actual numeric values of these similarities are, definitely, out of proportion; and more reasonable figures would be in the range of 30% to 40%, much lower than the coefficients obtained with the Euclidean matching method.

A second, more encompassing, deficiency of this approach, that could even help to explain the first one, has to do with factors that we deliberately left out of the model. Educational attainment, for instance, is one of them, and it could drastically change matching results, as several career paths have basic requirements in the form of specific degrees, certifications, years of experience, and so on and so forth.

Of course, these other aspects are all very important, and a full analysis of career compatibility should take them into consideration. That being said, here we decided to exclude them for two main reasons. The first is that adding such variables alongside the 120 competencies without modification to the matching method does not work, in purely practical terms, because the algorithm employed is not suitable to perform binary filtering based on key, necessary conditions, but rather to compute the distance between vectors.

The second reason is that these requirements are, actually, best conceptualized as *independent* coefficients themselves, that can, then, be multiplied, or otherwise combined with any kind of function to limit career compatibility scores. Moreover, skill set similarity, the sole object of this initial model, does not imply – or is even implied by – educational attainment, years of experience, etc. In other words, as these things are separate in the real world, so too they should separate in statistical models. And this "separation of concerns" is more parsimonious and leads to a "cleaner", theoretically consistent, framework.

At last, and most importantly, we must repeat that this Euclidean approach to career matching is an oversimplification for illustrative purposes; and that we have already developed more advanced methods to account for its problems. In fact, it is easy to derive better matching estimates only by tweaking the model presented above.

An immediate improvement, for example, would be to adjust weighting procedures to further emphasize the core competencies of comparison occupations by substituting the linear weights with a polarizing, logistic-like function. And one could also apply scaling functions to normalized Euclidean distances, in order to correct the similarity metric directly (e.g. by means of linear interpolations, root functions, etc).

Having said this, beyond some "quick fixes", more dramatic improvements require rewriting the entire matching algorithm to another format. But then again, the goal of this article was to provide an introduction to the crucial issue of quantitative career matching, not to exhaust the subject. In future works, we expect to be able to explain at length our sophisticated and performant models.

5 Conclusion

In this paper, we described the simplest approach to quantitative career matching, and illustrated its application with a sample of data from a robust source of occupational information, namely the O*NET framework. We also discussed a few of the fundamental issues involved in assessing career path compatibility, like competency weighting, and the problem of overqualification. In an effort to keep the article concise and accessible, however, we deliberately ignored many of the other complexities surrounding this subject.

Even so, we found our results to be mostly accurate, though not as precise as they would be had we employed superior methods. We highlight that the sample occupations were matched as "expected": engineers with engineers; physicists with scientists; credit analysts with other roles in the financial sector; and dishwashers with janitors, and "blue-collar" positions. Nevertheless, we noted, as well, that similarity scores were too high for some of these matches.

To tackle this inconsistency, we proposed an ideal, parsimonious solution, in which a number of independent coefficients ought to be calculated to separately account for the various aspects affecting compatibility. In addition, we also proposed a couple of more immediate "quick fixes" to adjust matching estimates.

Overall, as suggested by the article's title, this was an initial sketch to address a most important topic: that of rationally choosing a career. And, despite the basic model presented here not allowing to fully develop what "picking the right occupation" looks like statistically, we do hope and think it is, at least, a step in the right direction.

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Appendix

Table 8: Detailed Skill Sets

Competency	Mechanical Engineers	Physicists	Credit Analysts	Dishwashers
Engineering and Technology	87	86	13	0
Industrial Design	84	45	0	0
Applied Mathematics	79	94	68	0
Mechanical	78	28	0	12
Physics	73	97	0	0
Oral Comprehension	70	84	59	32
Reading Comprehension	70	84	57	30
Oral Expression	70	82	59	30
Deductive Reasoning	70	79	64	29
Pure Mathematics	70	79	59	14
Mathematical Reasoning	68	84	59	16
Written Comprehension	68	79	59	29
Complex Problem-Solving	68	70	43	30
Computers and Electronics	67	83	43	0
Natural Science	66	82	5	0
Operations Analysis	66	52	34	0
Active Learning	63	79	52	29
Information Ordering	63	71	52	30
Number Facility	61	79	63	16
Critical Thinking	61	70	57	30
Monitoring	61	57	43	30
Written Expression	59	80	57	23
Inductive Reasoning	59	79	59	29

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Table 8: Detailed Skill Sets (Continued)

Competency	Mechanical Engineers	Physicists	Credit Analysts	Dishwashers
Category Flexibility	59	73	50	29
Problem Sensitivity	59	70	57	29
Judgment and Decision	59	64	54	30
Originality	57	75	37	25
Writing	57	71	55	25
Native Language	57	70	60	38
Active Listening	57	68	57	32
Near Vision	57	57	61	34
Administration and Management	57	54	42	37
Quality Control Analysis	57	46	11	29
Chemistry	56	61	0	21
Fluency of Ideas	55	73	41	27
Speaking	55	68	57	30
Visualization	55	61	25	29
Systems Analysis	55	57	43	16
Systems Evaluation	55	55	45	16
Speech Recognition	54	57	50	30
Technology Design	54	48	0	0
Operations Monitoring	54	34	14	30
Instructing	52	66	34	20
Time Management	52	52	43	30
Troubleshooting	52	29	0	29
Education and Training	51	72	29	41
Administrative	51	40	59	0
Learning Strategies	50	71	36	18
Selective Attention	50	57	41	30

Continued on next page

Table 8: Detailed Skill Sets (Continued)

Competency	Mechanical Engineers	Physicists	Credit Analysts	Dishwashers
Persuasion	50	50	36	27
Coordination	50	48	36	30
Production and Processing	49	34	29	0
Speech Clarity	48	71	45	27
Flexibility of Closure	48	55	45	29
Perceptual Speed	48	46	45	30
Customer and Personal Service	48	37	39	38
Far Vision	46	52	30	32
Management of Personnel Resources	45	45	27	29
Speed of Closure	43	55	41	29
Negotiation	43	39	39	29
Social Perceptiveness	41	45	41	29
Service Orientation	41	43	43	29
Visual Color Discrimination	41	41	21	29
Management of Material Resources	41	32	13	13
Multitasking	39	41	29	29
Management of Financial Resources	39	30	27	11
Hearing Sensitivity	39	30	16	29
Memorization	37	48	34	21
Auditory Attention	37	32	21	29
Telecommunications	37	23	7	0
Equipment Selection	37	21	0	29
Installation	37	0	0	0
Building and Construction	36	15	16	0

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Table 8: Detailed Skill Sets (Continued)

Competency	Mechanical Engineers	Physicists	Credit Analysts	Dishwashers
Personnel and Human Resources	35	38	23	0
Public Safety and Security	35	26	15	26
Programming	34	55	14	0
Depth Perception	34	30	5	29
Operation and Control	34	9	0	30
Sales and Marketing	33	20	29	0
Finger Dexterity	32	29	25	34
Law and Government	32	28	54	28
Reaction Time	30	0	0	29
Transportation	28	12	0	33
Communications and Media	25	46	23	19
Economics and Accounting	25	26	74	0
Arm-Hand Steadiness	25	0	11	41
Repairing	25	0	0	29
Equipment Maintenance	23	0	0	29
Medicine and Dentistry	23	0	0	0
Geography	21	15	25	0
Biology	20	16	0	0
Trunk Strength	14	14	14	43
Manual Dexterity	14	0	9	52
Wrist-Finger Speed	9	0	0	21
Rate Control	5	0	0	32
Spatial Orientation	5	0	0	14
Psychology	0	28	10	0

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Table 8: Detailed Skill Sets (Continued)

Competency	Mechanical Engineers	Physicists	Credit Analysts	Dishwashers
Therapy and Counseling	0	21	0	0
Sociology and Anthropology	0	0	16	0
History and Archeology	0	0	13	0
Control Precision	0	0	7	32
Extent Flexibility	0	0	0	43
Static Strength	0	0	0	39
Multilimb Coordination	0	0	0	37
Stamina	0	0	0	32
Gross Body Coordination	0	0	0	30
Speed of Limb Movement	0	0	0	30
Response Orientation	0	0	0	29
Dynamic Strength	0	0	0	25
Gross Body Equilibrium	0	0	0	21
Glare Sensitivity	0	0	0	21
Sound Localization	0	0	0	14
Night Vision	0	0	0	14
Peripheral Vision	0	0	0	14
Explosive Strength	0	0	0	11
Dynamic Flexibility	0	0	0	0
Foreign Language	0	0	0	0
Philosophy and Theology	0	0	0	0
Fine Arts	0	0	0	0
Food Production	0	0	0	0

Source: O*NET, 2023.