A Person-Job Fit Index Using Multiple Intelligences Profiles: Calculating Risk for Chronic Relative Underperformance

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Abstract

In this article an index is constructed to compare profiles with each other, taking into account the interrelatedness of the different variables, and preserving the direction of fit.

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Summary

In this article an index is investigated which can express the fit between a job profile and a personal profile, which both make use of the concept of multiple intelligences (Gardner, 1983, 1993, 1999, 2002). The difficulties are (1) that even though the same conceptual framework is used to describe both the profile of capabilities that functions/jobs need and the profile of capabilities that persons have, the two measurements are not exactly the same in psychometric characteristics, and (2) that the index must be able to indicate whether a person is possibly *underperforming*, or might be overburdened by the function, while most methods result in distances or indexes in which the direction is lost. A method based on the Mahalanobis distance is developed, which measures the over- as well as the underscoring of a personal profile in regard to the job profile.

Introduction

The challenge we face in this article is how to compute a meaningful index which can express the difference between two profiles using the same underlying concept, but obtained with instruments different in psychometrics, with the objective to differentiate persons and use this in further analysis. A method is proposed that measures this difference, as well as the direction thereof. The index is supposed to indicate whether an employee is in danger of suffering from *chronic relative underperformance* (Jessurun et al., 2020). We have been unable to find a method of comparing profiles in the literature that has incorporated direction as well as distance.

The MIDAS™ (Shearer, 1996) is a questionnaire that provides an eight-dimensional space of intelligences: the ability to solve problems, render services or create products that are of value to a community – the definition of an intelligence according to Howard Gardner (1983, 1993, 2002). Gardner attempted to redefine intelligence in such a way, that all human endeavours could be captured in terms of multiple intelligences. He proceeded by defining a set of eight criteria to decide what might be coined as a separate intelligence, and after researching the literature with these criteria in mind, initially came with seven intelligences (Gardner, 1983) and later added an eighth (Gardner, 1993). The MIDAS questionnaire is a self-report instrument, that is *not* directly focussed on job-related abilities, but the questions within the instrument are general, and covering all aspects of life. For instance, for the musical intelligence, one of the questions is whether the person is able to sing in tune. One of the uses for the MIDAS profile is coaching on professional development (Shearer, 2013). For a short description of each intelligence see Table 1, and for how such a profile might look, see Figure 1.

Table 1

Description of the eight intelligences

Intelligence	Description
Linguistic	To think in words and to use language to express and understand complex meanings. Sensitivity to the meaning of words and the order among words, sounds, rhythms and inflections. To reflect on the use of language in every day life.
Logical-Mathematical	To think of cause and effect connections and to understand relationships among actions, objects or ideas. To calculate, quantify or consider propositions and perform complex mathematical or logical operations. It involves inductive and deductive reasoning skills as well as critical and creative problem-solving.
Visual-Spatial	To think in pictures and to perceive the visual world accurately. To think in three dimensions and to transform one's perceptions and re-create aspects of one's visual experience via imagination. To work with objects effectively.
Musical	To think in sounds, rhythms, melodies and rhymes. To be sensitive to pitch, rhythm, timbre and tone. To recognize, create and reproduce music by using an instrument or voice. Active listening and a strong connection between music and emotions.
Kinesthetic	To think in movements and to use the body in skilled and complicated ways for expressive and goal directed activities. A sense of timing, coordination for whole body movement and the use of hands for manipulating objects.
Interpersonal	To think about and understand another person. To have empathy and recognize distinctions among people and to appreciate their perspectives with sensitivity to their motives, moods and intentions. It involves interacting effectively with one or more people in familiar, casual or working circumstances.
Intrapersonal	To think about and understand one's self. To be aware of one's strengths and weaknesses and to plan effectively to achieve personal goals. Reflecting on and monitoring one's thoughts and feelings and regulating them effectively. The ability to monitor one's self in interpersonal relationships and to act with personal efficacy.
Naturalistic	To understand the natural world including plants, animals and scientific studies. To recognize, name and classify individuals, species and ecological relationships. To interact effectively with living creatures and discern patterns of life and natural forces.

Adapted from Shearer (Shearer, 1996)

Multiple intelligences theory has been applied to the workplace (Green et al., 2005; Hoffman & Frost, 2006; Martin, 2000, 2003; Mohamed & Awang, 2015; Noruzi & Rahimi, 2010; Palthe, 2019), and the neuropsychological evidence for the model is becoming gradually stronger (Shearer, 2020; Shearer & Karanian, 2017).

The MIDAS-JOB (Jessurun & Weggeman, 2015) is a questionnaire, derived from the MIDAS and work by Martin (2000), that attempts to describe jobs or functions within the same eight-dimensional intelligences-space. The questions in this instrument are as general as possible, but focused on work-related situations. For instance, "Does the job require recognition of sounds", as an example of an item for musical intelligence.

The challenge we are confronted with is how to *meaningfully* compare these similar, but psychometrically different instruments, in order to make this comparison useful, for instance to recognize the possibility of *chronic relative underperformance*. This challenge is even more complicated, because there are differences in meaning for each individual MIDAS-profile. They are based on self-report, therefore *high* does not mean the same for each person. Based on a job-profile within the field of mental health care and on a set of profiles from individuals within that work-setting, we will present you with a method to get a meaningful comparison.

The MIDAS™ profile

A MIDAS profile is presented in Figure 1. The MIDAS scales are simple percentage scales, and range from 0 to 100. Each of the 118 questions is answered on a 5-point Likert-scale, and the score on a scale equals the total of item-scores divided by the number of items in the scale, multiplied by 100. The questions are presented per intelligence, so a person knows on what intelligence he or she is reporting. Apart from these scales, based on a factor-analysis

Figure 1. An example of a MIDAS-profile

on several hundreds of profiles, Shearer (1996) incorporated three 'intellectual style scales', *general logic, leadership* and *innovative.* Also, the main scales were all broken down by factor analysis in smaller sub-scales, sometimes using questions from other intelligences, to deliver a deeper level for e.g. coaching. Importantly, the MIDAS assessment and profile were meant to be *individual* and *idiosyncratic* measurements. When using the MIDAS for coaching, the interpretation protocol actively discourages comparing your profile directly with someone else's, because your score of 60 might mean something differently than the 60 by that person. The interpretative process is part of process called the 'MIDAS validation interview'.

For the task described here, comparing with the job-profile, which might precede the validation interview, we *do* need to revalue the profile-scores in such a manner that the scores do mean more or less the same.

A MIDAS-JOB profile is also represented as a set of percentage scores. The difference is that the MIDAS-JOB profile is based on what several people, e.g. a group of professionals themselves or a job assessor, assessed about what a function would need on each of these items on the intelligences in terms of (1) importance for the function, and (2) how often it is needed. The job-profile is the mean of all those assessments on the eight dimensions.

The rationale for determining a Risk for Chronic Relative Underperformance

To function well humans need to be in relatively healthy circumstances. At the moment the work force in mental health care, education, and other professionals is ageing fairly rapidly (Aiyar et al., 2016), and the importance to create a healthy environment within organizations becomes even greater than normal morality would ask. When a person is not challenged enough, according to capacities which she or he possesses, chances are that the disequilibrium in his mind which results from this, will lead to a state of lessened functioning, *chronic relative underperformance* (Jessurun et al., 2020).

An index such as developed here is intended to help organizations to identify employees at risk, to find out what kind of challenges they need (by examining the MIDAS with them in an exploratory way, and thus contributing to the recombining of their goals and that of the organization. This is why an instrument, which main use is self-exploration and self-development – the MIDAS –, is connected with the MIDAS-JOB in this way. The second step after identifying someone at risk would need to be the MIDAS validation interview. What is striven after is therefore not, in the words of Weber (1922), an *instrumental goal* (zweckrational), but a *value goal* (wertrational).

Set of data

The MIDAS-JOB has been used to attain profiles of employees in a community mental health care service in the Netherlands (Jessurun & Weggeman, 2015), psychiatric nurses, psychologists, registered psychologists, psychotherapists and clinical psychologists. For our purposes we will use the mean profile across all assessed functions. For the personal MIDAS-profiles we will use a small set of data obtained from employees working in another community mental health care service (see Table 2). The people from whom these data were obtained do not have any evident issues with functioning in their profession, they are functioning 'within parameters'.

Table 2
Job profile and MIDAS profiles from seven mental health care workers

	LIN	INTER	INTRA	LM	VS	MUS	KIN	NAT	LEAD	GL	INNOV
P	70	78	76	45	17	22	24	20	-	-	-
#1	49	59	57	50	62	40	43	36	59	61	44
#2	53	63	45	41	48	29	33	53	63	47	47
#3	72	68	60	43	39	30	50	67	79	54	58
#4	56	62	51	37	35	48	27	47	62	-	49
#5	45	54	46	29	44	48	44	44	61	39	42
#6	29	64	39	28	39	16	58	28	57	41	33
#7	34	54	47	36	25	32	27	19	56	49	22
Mean	48	61	49	38	42	35	40	42	62	49	42

First impressions

The seven individual profiles are obtained from trained professionals, though at different levels of experience and expertise. At first sight, if we compare their profiles with the job-profile (P) above , the conclusion is that all of them are below stats on those things that matter (in the case of this job profile: Linguistic, Interpersonal and Intrapersonal). The validity of that conclusion is gainsaid from what the main author knows about their performance (as stated above).

This shows the dissimilarity between the job-profile metrics and the individual profile metrics. As for the individual profiles we are faced with some problems as well. For instance, respondents #6 and #7 have fairly low scores overall; which might mean that they are overly critical about themselves. They seem to fit the job-profile not so well. The most fitting profile seems to be – to the human eye – the profile of respondent #3.

Making sense of the profiles

Correlations?

One of the methods to compare the individual profiles with the job profile is by correlating them – a similarity measure. There are several methods to do this, and in Table 3 we show the pearson, kendall, and spearman correlations. The conclusions of the results of correlation is that this is not very helpful. When looking at the numbers, one of the profiles that at first sight seemed to fit *the least* now shows the *highest* correlation (nr. #7). What a correlation means is that the profiles are more or less of the same shape, but is that really important to know?

Table 3
Job x Person MIDAS correlations

R		Pearson	Kendall	Spearman
#1	value	0.4960623	0.4285714	0.3095238
	p	0.2112	0.1376	0.4556
#2	value	0.5405023	0.3273268	0.3113828
	p	0.1666	0.2618	0.4528
#3	value	0.6305623	0.4285714	0.5952381
	p	0.09371	0.1376	0.1195
#4	value	0.7158899	0.5714286	0.7142857
	p	0.04581	0.04776	0.04653
#5	value	0.2476567	0.4157609	0.5123475
	p	0.5543	0.1613	0.1942
#6	value	0.3178484	0.3706247	0.4458155
	p	0.443	0.2089	0.2683
#7	value	0.8694534	0.7857143	0.9285714
	p	0.005032	0.006493	0.000863

In the end what we need to establish is whether the person with a certain MIDAS profile fits for a certain function with a specific MIDAS-JOB profile; and also if there is a danger for *(chronic) relative underperformance*. What we need to understand is that the MIDAS-JOB expresses more *how important* the intelligence is to the function, while a MIDAS profile gives an indication of how much of it a person reports he or she has.

Unifying the MIDAS profiles

When we had our first look at the profiles, it became apparent that some people score lower overall than others, some profiles have low and high scores, and experience has told us that there are people who score high in everything. The problem is therefore, that the profiles are not sufficiently comparable. We need a rational formula to correct for this and make the profiles more universal. We know that all these profiles are from people who are functioning well enough, so it is reasonable to transpose their scores. The MIDAS scoring system has been developed in such a way that the mean scores gravitate around 50 (e.g. for some Asian countries the answering categories were reworded somewhat to raise scores, because they are relatively modest in there assessments, see Shearer, 1996).

The first step proposed in unifying the profiles is using the individual mean and standard deviation (so across the intelligences per respondent), leading to Table 4. We have no other objective data on these individuals, to use for normalizing their data.

Table 4
Individually normalised scores

R	LIN	INTER	INTRA	LM	VS	MUS	KIN	NAT
#1	-0.053	1.011	0.798	0.053	1.330	-1.011	-0.692	-1.437
#2	0.660	1.555	-0.056	-0.414	0.213	-1.488	-1.130	0.660
#3	1.193	0.933	0.414	-0.690	-0.949	-1.533	-0.235	0.868
#4	0.914	1.430	0.484	-0.720	-0.893	0.226	-1.581	0.140
#5	0.107	1.388	0.249	-2.171	-0.036	0.534	-0.036	-0.036
#6	-0.532	1.626	0.085	-0.593	0.085	-1.333	1.256	-0.593
#7	-0.022	1.712	1.105	0.152	-0.802	-0.195	-0.628	-1.322

We normalize all individual profiles such that they have a mean of 15 and a standard deviation of 15. The mean of 50 refers to the mean score of global MIDAS profiles. The standard deviation chosen is the one which standard intelligence tests, such as the Wechsler scales, use. The values chosen make it likely, that the new scores will remain between 0 and 100.

Table 5
Unified MIDAS profiles

R	LIN	INTER	INTRA	LM	VS	MUS	KIN	NAT
#1	49	65	62	51	70	35	40	28
#2	60	73	49	44	53	28	33	60
#3	68	64	56	40	36	27	46	63
#4	64	71	57	39	37	53	26	52
#5	52	71	54	17	49	58	49	49
#6	42	74	51	41	51	30	69	41
#7	50	76	67	52	38	47	41	30

Having made these transformations we can observe (see Table 5) that overvaluation and undervaluation of the profiles seems to be corrected, and all profiles seem to make more sense in comparison with the job-profile. What we do not have at this point is a single index that expresses the amount of fit between the job profile and the personal profile. The correction made is far from optimal or safe, because it depends on there being a variance within the personal profile. A person scoring 70 for each intelligence, or 40 for each intelligence, would end up with an individual standard deviation of 0, and both would have unified profiles of 50 for the whole intelligences-space. This effect can be seen in a mild form for respondent #3, whose scores have mainly dropped.

Unified job profile

If we make z-scores of the job-profile, just as we did with the personal profiles, we can determine which intelligences are the most important within the profile. We see (Table 6) that the Linguistic, Intrapersonal, and Interpersonal intelligences are really important for the functions in mental health care, that Logical-Mathematical should be available, and the rest of them are "unnecessary".

Table 6
Unified Job Profile

Intelligence	z-score	unified score
LIN	0.96838654	65
INTRA	1.26635163	69
INTER	1.19186036	68
LM	0.03724564	51
VS	-1.00563218	35
MUS	-0.81940400	38
KIN	-0.74491272	39
NAT	-0.89389527	37

Also, based upon this normalization, we can redefine them, so that two-thirds of these scores fall within the range of 35 and 65 with a mean of 50.

Distance measures

In the library *philentropy* (Drost, 2019), a set of scripts for the R statistical package, 46 measures are defined to calculate differences or similarities for comparing probability functions. Three of the most known distance measurements are the Manhattan distance (going from one point to the other restricted by only being able to go north, south, west or south), the Euclidean distance (a straight line between two points) and the Minkowski distance (something in between, if using a weight between 1 and 2).

Table 7
Three common distance measures between MIDAS Job profile and seven individual profiles

Profile	Manhattan	Minkowski (weight: 1.54)	Euclidian
#1	74	46.55261	40.29888
#2	92	48.52459	37.94733
#3	76	41.96035	33.85262
#4	71	38.30603	29.88311
#5	119	62.36029	48.63127
#6	113	59.67932	46.67976
#7	45	25.27566	20.46949

Within the dataset used, there is not much difference between these measures to determine fit (see Table 7). The ranking of each is the same. In all cases the shortest distance is for #7 (just as with the correlations the ‘best fit’), the largest for #5. Even though computing these differences seem like a good way to compare the similarity between the individual intelligences-space and the function intelligences-space, it will again not lead to a result that can be used for P-E fit.

Mahalanobis Distance

The Mahalanobis Distance (Mahalanobis, 1936) is a distance measure that takes into account the correlations in the dataset. For our purposes this is important, because there are correlations between the eight intelligences across respondents (see Table 8). Since the application of this distance is not related to outlier detection, which use has been found problematic (Leys et al., 2018), we can use it safely.

Table 8
Correlations between MIDAS intelligences

	MUS	NAT	VS	LM	INTRA	KIN	LIN
NAT	0.20	--					
VS	0.18	0.50	--				
LM	0.13	0.45	0.61	--			
INTRA	0.12	0.35	0.56	0.74	--		
KIN	0.11	0.20	0.43	0.27	0.32	--	
LIN	0.30	0.29	0.29	0.36	0.52	0.20	--
INTER	0.14	0.13	0.27	0.27	0.56	0.32	0.56

The Mahalanobis Distance compensates for those correlations when determining the distance between a reference point P (our job-profile) and the individual profile. Since the intelligences are *not* statistically independent in reality (even though conceptualized thus by Gardner), the Mahalanobis is most appropriate[1].

Table 9
Mahalanobis Distances for the seven profiles

#1	#2	#3	#4	#5	#6	#7
9.01	7.43	7.62	6.86	26.12	15.37	5.48

1 To compute the covariance table needed for the Mahalanobis Distance, the data are used that have been obtained on a diverse set of subjects (teachers, students, coachees health care workers and so on), which has been obtained between 2011 and 2015.

Here the shortest distance is for subject #7, and again the largest difference is for #5. And this distance measure does not – just as the others – take into account *over*- or *under*scoring (see Table 9).

Intermediate conclusions

The previous analysis shows that there is no easy way to determine fit, without losing important information of the direction of the fit.

- Correlations do say something about the similarity in form of profiles. A high correlation may mean total overlap between two profiles, or that the one is on all intelligences higher or lower in about the same amount. For our purposes it gives little useful information.
- We have to take into account the fact that two individual profiles may differ in meaning, because of them being the result of self-report. There are ways of transforming these, to make them somewhat more uniform, but these formulas have there caveats as well.
- Distance measures are alas not very informative as well, because they quadrate negative distances into positives, just as the positive distances.
- As has been said before, the job-profiles more or less express the importance of an intelligence. So we need to find out how to express this importance related to the personal profile.
- We have to take into account, that even though people may be 'low scorers', or 'high scorers' that this does mean something. The unification transformation subtracts important information as well, and we will have to find a method to repair this.

Including the direction of the fit per intelligence

Subtracting the job profile from the personal profile gives a matrix with the direction of fit. This direction can be used to make *two* separate fit indices per respondent. For respondent #1, this would mean an index for the scales LIN, INTER, INTRA, MUS and NAT, and one for VS and KIN; and so on. The Mahalanobis distances per profile with the distinction between under- and overscoring gives the results in Table 10.

Table 10

Direction of fit

R	LIN	INTER	INTRA	LM	VS	MUS	KIN	NAT
#1	-16	-4	-6	0	35	-3	1	-9
#2	-5	4	-19	-7	18	-10	-6	23
#3	3	-5	-12	-11	1	-11	7	26
#4	-1	2	-11	-12	2	18	-13	15
#5	-13	2	-14	-34	14	23	10	12
#6	-23	5	-17	-10	16	-8	30	4
#7	-15	7	-1	1	3	9	2	-7

Inspecting the results in this table, we can observe the following:

1. When the distance of the over-scoring intelligences is higher than the underscoring intelligences, we might assume that this person might be underperforming as to his own abilities.
2. The number of intelligences under- and overscoring differs per person. For instance for person #1, 6 underscoring intelligences total up to a difference of 4.0, and 2 overscoring intelligences sum op to a difference of 3.76. Thus, it is logical to compute the *mean Mahalanobis* distances for both under- and over-scoring (0.67 and 1.88), and use these (see Table 11).

Using this approach, we would say that person #1, #2 and #3 are considered at risk, and perhaps #1 more so than #2 and #3, for chronic relative underperformance (CRU), when working in a mental health job.

Table 11
Mahalanobis Distances for Under- and Overscoring Intelligences

	Total	Under	Over	#Under	#Over	Mean Under	Mean Over	Ratio = O/U	Diff. = U-O
#1	9,01	4,00	3,76	6	2	0,67	1,88	2,82	1,21
#2	7,43	2,52	2,14	5	3	0,50	0,71	1,42	0,21
#3	7,62	1,38	2,19	4	4	0,34	0,55	1,59	0,20
#4	6,86	2,42	1,05	4	4	0,60	0,26	0,43	-0,34
#5	26,12	13,76	1,98	3	5	4,59	0,40	0,09	-4,19
#6	15,37	5,07	3,85	4	4	1,27	0,96	0,76	-0,31
#7	5,48	1,10	0,67	3	5	0,37	0,13	0,36	-0,23

Adjusting bias for high or low profiles

Even though in this small sample there is no example of consequently high or low scoring persons, in our experience this does happen. There are for instance extremely multitalented people, who do not only have a professional career in science, but apart from that are gifted musicians and sometimes visual artists, and who achieved a first dan in a budo sport as well. For instance, consider the profile in table 12.

Table 12
High scoring profile

	LIN	INTER	INTRA	LM	VS	MUS	KIN	NAT	Mean	Sd
HSP	86	91	80	74	83	41	65	94	76.75	17.15
unified	58	62	53	48	55	19	40	65	50.00	15.00

Unifying these kind of profiles seems to do little justice to the specifics of this high scoring person. The more, because it seems to be a valid profile, because of the drop for Musical intelligence, suggesting that this person does really make an effort to score his abilities thoughtfully, and is not someone who just fills out everything in the high ranges (which still does not say that someone having all high scores has not provided a valid profile).

Table 13
Mahalanobis Distances for a High Scoring Profile

	Total	Under	Over	#Under	#Over	Mean Under	Mean Over	Ratio = O/U	Diff. = O-U
HSP	11,59	3,58	2,97	5	3	0,72	0,99	1,38	0,27

What we see in Table 13, is that this profile *does* register as one with some chance of CRU, though – contrary to the initial intuition, which expected us it to be highest – not as high as subject #1.

When we discussed unifying the profiles, this was mainly based on the presupposition, that low scoring profiles were probably biased, on the argument that all these people are working as adequately functioning mental health care professionals. The unifying led to raising these profiles a bit. The result is that then high scoring profiles are underestimated. We suggest unifying profiles with a mean score of higher than 50 by using there mean score instead – so transforming the standard scores to the mean score plus the standard score times 15, and then following the procedure described above. The results are shown in Table 14.

We see that this high scoring profile is now only scoring on the over-scoring distance, and that profile #3 gets a bit more pronounced. This change is in the direction, therefore, that we were after. This adjustment might be used in a population of which we know that they are already functioning in the job that the profile describes; for a general population this should not be applicable.

Table 14
Mahalanobis Distances for Differential Unified Profiles

	Total	Under	Over	#Under	#Over	Mean Under	Mean Over	Ratio = O/U	Diff. = O-U
#1	9,01	4,00	3,76	6	2	0,67	1,88	2,82	1,21
#2	7,43	2,52	2,14	5	3	0,50	0,71	1,42	0,21
#3	7,92	0,82	2,76	4	4	0,21	0,69	3,35	0,48
#4	6,86	2,42	1,05	4	4	0,60	0,26	0,43	-0,34
#5	26,12	13,76	1,98	3	5	4,59	0,40	0,09	-4,19
#6	15,37	5,07	3,85	4	4	1,27	0,96	0,76	-0,31
#7	5,48	1,10	0,67	3	5	0,37	0,13	0,36	-0,23
HSP	20,44	NA	20,44	0	8	NA	2,55	NA	NA

How to determine Risk for Chronic Relative Underperformance

Based upon the exercises we did on the individual profiles in relation to a single job profile, we would like to offer the next propositions for an index of Risk for Chronic Relative Underperformance (rCRU):

1. If the individual profiles are from a population working in the area of the job profile to be tested against, we propose to use the differentiated unified profiles; this is to take into account that some people are biased towards themselves negatively, and that (since they are already working in a job-profile related function) are qualified for the job. The differentiated unification adjust for high scoring profiles, which otherwise would gravitate to the mean. In a general population we would propose to use the undifferentiated unified profiles.
2. For each person a mean Mahalanobis distance is computer for
    1. scales on which he/she scores higher than the job profiles, and
    2. scales on which he/she scores lower than the job profiles.
3. We assume the person at risk for chronic relative underperformance, if the difference between the over- and underscoring scales is a positive number; the assumptions is

that the higher the difference the higher the risk; or when there are only over-scoring scales that there is a high risk.

Computing the over-scoring and underscoring distances on a larger sample

To see how this method holds up when computing the over-scoring and underscoring distances on another sample, it was tried on a sample of 895 MIDAS profiles. These were individual profiles of a diverse group of people from different sources (students, teachers, coachees, workshop participants, health care professionals), so an undifferentiated unification was used. This leads to the results in table 15.

Table 15

Results of the procedure on a sample of 895 adults

	Total	Under	Over	#Under	#Over	Mean Under	Mean Over	Ratio	Diff.
Mean	17,94	6,01	3,82	3,95	4,05	1,62	1,05	1,55	-0,52
Stdev	8,50	4,31	2,88	0,90	0,90	1,34	0,91	3,05	1,55

Over- and underscoring on this sample *is* correlated (t = -2.8194, df = 812, p-value = 0,004929), but at a very low level (-0,09845939). In the sample there are several instances for which either the over-scoring distance or underscoring distance could not be computed, which explains the degrees of freedom of 812.

One of the ways to assign the risk of CRU in this sample would be to classify all persons with a Difference score of 1,03 (mean plus one standard deviation) or higher as being at risk (about 149) or two standard deviations (about 21 persons).

Conclusion

This paper proposes a method to compare individual profiles with a standard profile and generate a distance value between the two profiles, which can be used in statistical analysis. In this case, we apply the proposed method to the model of Multiple Intelligences, and focused especially on how to generate an index on Risk of Chronic Relative Underperformance, but it could be possible the same method to focus on Risk of Overburdening as well by only using the Underscoring Mean Distance.

Regaining the direction of differences when comparing profiles is explicitly useful, when we need to know whether someone is performing below or higher than parts of a profile. In regard to the theory of multiple intelligences, which in a way describes in broad categories all capabilities we need for survival – one of the criteria for an intelligence is that it must have an evolutionary meaning (Gardner, 1983) –, and which we described in relation to *chronic relative underperformance*, this might be a way to pinpoint possible areas of development through which a person may yet go, even though it seems to be closed down. However, there may be dangers as well, for instance when the index should be used for personnel selection, with the intent to weed out any possibly potentially problematic employees. We do not think that the MIDAS nor the MIDAS-JOB, and therefore the resulting rCRU-index, are strong enough questionnaires to do that. We can imagine when this method is used to identify people at risk, that for those the MIDAS interview (or any other entry point to start coaching) may be helpful.

We assume that the same method of determining distances and ratio's can be used with other questionnaires, describing profiles. The MIDAS is developed to assess intellectual abilities. The Minnesota Multiphasic Personality Inventory (Hathaway & McKinley, 1951) for instance, is the major personality inventory used within mental health care, and delivers a profile of several variables. Scoring higher on a variable usually means that some psychological problem is present. Specific ‘profiles’ can describe specific psychological constellations. The proposed method could also be used, for instance to compute a Risk for Neurotic Problems, comparing individual profiles with the ‘typical’ neurotic problems profile.

The main contribution of this method is, that it takes into account the direction of the distances, by splitting them in positive and negative direction. In this way valuable information is preserved.

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