THE CONCEPT OF AN AI-BASED EXPERT SYSTEM (ATOM) FOR PREDICTING JOB SUCCESS

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Summary

Background and Aims: This article offers a brief prospective exposition of the other articles published in this special issue on artificial intelligence (AI)-based expert systems for predicting job success in general. It also focuses on a concrete implementation of such a system, developed by us. Apart from providing a broader perspective on the possibilities and limitations of applying AI in various fields of human resources management (HRM), such as recruitment, selection, employment, training, performance monitoring/management, wages, labor relations, occupational safety and health (OSH), etc., this text serves as the foreword by the editor of this special issue.

Recent AI applications supporting HRM are predominantly limited to recruitment; in other fields, companies still rely on traditional methods. Given the observed underperformance of HR personnel in workforce selection decisions, we have developed an AI-based system primarily for this task, known as ATOM (Artificial Intelligence for Testing Occupational success of Manpower). ATOM not only supports workforce selection but also effectively aids in recruiting and, to some extent, OSH.

The core function of ATOM is to "learn" the relationship between suitable predictors (variables suitable for predicting the future job success of applicants) and relevant success criteria scores for the given job. A notable feature of ATOM that provides outstanding efficiency and flexibility is its use of multiple machine learning (ML) algorithms running concurrently, with the results of the best-performing algorithm being accepted.

Keywords: artificial intelligence (AI), machine learning (ML), human resources management (HRM), job success, ATOM

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Applying AI for supporting workforce selection: The state of affairs

When a new technology, like AI, starts getting noticed, subsequent hype is almost inevitable. As Kordon (2020) puts it, although "data is the new oil", it is time already in certain areas for the transfer from hype to real competitive advantage. Such a main area nowadays is, among many others, companies' staffing.

From a wider perspective, the proper handling of HR (human resources) at companies and other working organizations is of decisive importance. Namely, the HRM (human resources management) covers the main fields of recruiting, selection, employment, training, performance monitoring/management, waging, labor relations, and occupational safety and health (OSH). While *recruitment* refers to the process of searching for potential applicants (and encouraging them to apply for an actual job), *selection* is the process of finding the best candidates from the shortlist created by appropriate preliminary testing. Selection is a decision-making process, which is still made mainly by humans, but appropriate artificial intelligence (AI) applications have tremendously high, yet far unutilized potential.

AI applications recently are being used to support HRM, still mainly in the field of recruitment. After Wheeler and Buckley (2021), it can be stated that "[c]ompanies still use traditional recruiting methods like job fairs, college recruiting, newspaper ads or billboards, and referrals; but the availability of data from multiple sources allows companies to proactively seek applicants who they then recruit to apply for jobs" (p. 60). Wheeler and Buckley (2021) later continue, "[s]ocial media sites like Facebook and LinkedIn allow digital recruiters to hyper-target possible applicants based upon the very information that users of those sites self-disclose" (p. 62).

Experience shows that humans, like HR persons, usually underperform in workforce selection decisions. We agree with Eubanks (2022), who states, "[a]dmit it: we're bad at selection. The data shows that the common ways we interview and many of the methods companies use to rank candidates (school attended, college grades, or other demographic data) are highly unreliable statistically. Translation: they are terrible as a gauge for whether someone can do a job or not" (p. 109). This is a strong argument for developing AI applications to support workforce selection. In addition to the advantage of possible better statistical reliability, such AI-based systems work incomparably quicker than humans do, and consequently, potentially much cheaper too.

The traditional (not AI-supported) workforce selection methods have serious validity limits. Barrick et al. (2001) state that even the personality construct of the best predictive validity – *"conscientiousness"* – usually has only a correlation of 0.20–0.25 with job performance.

Concerning the selection process two main biases are distinguished usually.

The first originates from the applicants, who are willing to show themselves as better than they are. This tendency might result in faked personality inventories and intentional fraud causing misinterpretation of resumés by HR coworkers, as Henle et al. (2019) published. The same distortions appear also in Assessment Centres, McFarland et al. (2003).

The second lies in the applied methods – König and Langer (2022) – since most personnel selection methods involve human decisions that are inherently error-prone.

In our opinion, however, there also exists a third bias. The source of this bias relates to the question: "Have we chosen the best procedure available in terms of given output-input relationships?"

The first bias remains henceforward in the cases of AI-supported methods also, while the second one, at least in principle, can be reduced by applying appropriate AI-driven methods. Reducing the third bias is only possible if a proper variety of procedures are used, either sequentially or simultaneously, and the results of the best performing one are accepted. Although this approach requires increased resources, it is already quite feasible for AI-driven methods running on today's quick computers. Notwithstanding, we have not found in the literature AI-based methods operating on this principle. Our system, however, to be reviewed in the next section, is based on this principle: it runs simultaneously many machine learning (ML) algorithms, and the outputs of the "winner" (the best performing one) are considered as final results. Thus, our system can effectively reduce this third type of distortion.

The rationale and functional fundamentals of ATOM

While the primary goal of psychology, as a scientific discipline, is to understand and explain human behavior, the practical fields of applied psychology – among them also work and organizational psychology – are much more interested in prediction (Yarkoni & Westfal, 2017). The explanation of the processes is usually not the goal of work and organizational psychology. Instead, its focus is usually on practical decision-making. ML methods can maximize the prediction accuracy of the models. While doing so, most of the time they do not provide an understandable explanation for how the phenomenon works. In this case, although it may provide a precise prediction for the given phenomenon, we will usually not know which variables played a role in the outcome and to what extent. This is the reason why we launched a project to develop a job success prediction system, for clearly practical purposes, based on AI and ML algorithms.

Of the HRM fields mentioned in the preceding section, our system, ATOM (Artificial intelligence for Testing Occupational success of Manpower) can mainly support recruiting and selection, and partly also OSH (refer to Izsó, Berényi & Pusker, this special issue). This special issue focuses on workforce selection by ATOM.

ATOM, developed by us at CIVIL Plc, is an AI-based expert system working on the web platform. The basic function of ATOM is to "learn" the relationship between suitable *predictors* and relevant *success criteria* of a certain job.

A predictor in this context is a variable suitable to predict the future job success of applicants.

Predictors can typically include, among many others: qualifications, relevant work experience, job-specific skills (e.g., driving license, computer proficiency, ability to speak a particular language), certain test scores, objective parameters measured by electromechanical or computerized aptitude-testing devices or work simulators, etc.

The job *success criteria* can typically be:

- actual quantitative and/or qualitative production data (however, such data – for theoretical or practical reasons – are not available for many jobs),

- management's scores on the employee's performance (the disadvantage of these is that they are generally not statistically reliable enough, primarily due to the so-called "halo effect" and "leniency" and "severity" biases).

The definition of well-founded success criteria should normally be an integral part of the job analysis.

Job analysis means the systematic collection and organization of information about the specific requirements (criteria) of the given work task for the employee. Therefore, it is desirable to compile so-called "job profiles" that contain these criteria in a well-structured way. If such criteria are available and appropriate – strongly correlated – predictors can also be found for them. Based on these predictors, the person's success in the given job can be predicted with a high probability.

While compliance of a candidate with the criteria can only be established later during the actual work activity, the predictors can be determined or measured by an instrument or simulator even before employment with relatively simple tools and at low cost.

ATOM can be applied if valid predictors are available for at least 100 employees already working in the given job, whose job success, varying from failure through medium to excellent success, is also available.

Then the ML algorithms in the core of ATOM can "learn" the relationship between the predictors (as input variables) and the criteria of job success (output variables). Based on the model built this way, ATOM later can predict the expected job success of new candidates from the predictors only, with a high probability.

A novel feature of ATOM is – as mentioned above and described in the 2nd article of this special issue (Gergely & Takács: this special issue) in more detail – that in its core many machine learning (ML) algorithms run concurrently, and the results of the best performing algorithm are accepted.

As can be read also in (Gergely & Takács, this special issue), the core of ATOM works via the type "supervised learning" of the ML, where the "training example" is a set of input-output data pairs. The goal of the process is classification, that is, to estimate probabilities for each new candidate falling into different success categories and then based on these, to determine success categories themselves solely from the predictors.

In the last, 6th article in this special issue (Izsó, Berényi & Takács, this special issue) real-life case studies are shortly presented. Here, applying the proposal of Tasdemir (2015), ROC analysis is used for evaluating ATOM's classification performance.

The main services of ATOM

ATOM package, corresponding to the three main user types, has three functionalities (sets of functions).

The employees' functionalities, by the help of which new candidates for a given job (or in the case of organization development, employees already working in the organization) can fill in the designated questionnaires or administer some simple instruments to themselves. The data collected this way can be processed from several points of view and in several directions. Among others, candidates – based on an automatic evaluation by ATOM – are provided with personal feedback about their strengths and competence fields still to be developed, and in case of interest, about jobs realistically available for them.

The employers' functionalities support the employers' HR and other co-workers in manpower selections (and later also in employees' career orientation and monitoring) by providing them with candidates' success probabilities for each success category.

The experts' functionalities support analyst experts – independent of the employer company –, with sophisticated analysis interaction possibilities and detailed feedback on the key competencies which have a significant impact on the success in the given job.

The sophisticated AI functions of ATOM, described in the previous section, support mainly interactions through the latest two (the employer's and the experts') functionalities.

The traditional process of workforce selection and supporting this process by ATOM

The traditional workforce selection with the help of work psychologists and/or occupational safety and health (OSH) professionals

The selection process is based on the following two kinds of expertise:

- *The expertise* (including relevant tacit knowledge) existing within the organization concerning the content of the given job, performance criteria, typical local conditions, and problems.
- *The expertise of work psychologists and/or OSH professionals* concerning human features and competencies (personality traits, work physiological characteristics, possibilities, and limits, etc.) and their assessment methods.

Both kinds of expertise – complementary to each other – are necessary. However, these two parties could only acquire their missing knowledge by investing a quite significant effort, and rather slowly and costly. Although there are examples that specific organizations (such as armed forces, nuclear power plants, airline companies, etc.) employ full-time psychologists who function in the organization and therefore have more profound knowledge concerning critical jobs, these are just exceptions.

Typical steps of traditional workforce selection:

- the organization invites work psychologists, OSH professionals, or a vocational advisor company who try to learn the work content and performance criteria;
- the invited experts assign competencies to the given job and also assign assessment methods (usually psychological tests or aptitude tests assessed by measuring devices) to these competencies;
- the organization (usually represented by its HR co-workers) together with the invited experts, organizes and executes the assessments (usually psychological testing or aptitude tests assessed by measuring devices);
- the invited experts compile personal expert reports;
- HR co-workers try to utilize these expert reports in their employment decisions.

All these steps are relatively slow, work-intensive, and costly. Slowness is especially problematic since it often happens that by the time the organization informs candidates about the results and employment decision, they are already employed by another company.

The workforce selection process supported by ATOM

Proposed steps of manpower selection supported by ATOM:

- the organization invites a company that possesses an ATOM package and also ATOM experts (ATOM experts have to learn the work requirements only very broadly);
- the invited ATOM experts apply a broad-spectrum general personality test, and therefore there is no need to select measuring instruments (except if unique competencies have to be assessed by particular questionnaires or measuring devices);
- the HR co-workers, together with the invited ATOM experts, organize and execute the assessments (if it is done online, it can be speedy);
- ATOM automatically – if only questionnaires are used – generates and forwards reports both to candidates and HR co-workers in real-time;
- HR co-workers utilize these reports in their employment decisions.

The process is mainly automated. Therefore, it is much less work-intensive, less expensive, and much faster.

Comparing traditional and ATOM-based manpower selection

The ATOM-based process also utilizes the two kinds of expertise mentioned above, but it is much simpler, quicker, and more reliable, since

- there is no need for organization-specific expertise other than the actual degree of job success for the employees included in the "learning sample";
- and the expertise of vocational psychologists/physicians is utilized automatically via the algorithms of ATOM.

Potential possibilities of ATOM for applying in areas other than predicting job success

Although ATOM was developed as a sophisticated tool for predicting job success, under certain conditions, ATOM can also be applied in other areas. If we choose another goal function instead of job success, and we select predictors that are appropriate to this very other goal function, ATOM will, of course, produce predictions of the same accuracy as in the case of predicting job success. In short, it can be stated that ATOM is applicable to any prediction problems isomorphic with the predictors → job success schema.

The following *Table 1.* shows several examples from the possible many – from very different areas – for predictions that can be carried out by ATOM, and in which not job success is the goal function.

This table is to be interpreted in the following way: the goal function is a purposefully operationalized categorical measure of whether the examined event will occur within a predetermined period. The predictors are variables that influence these occurrences.

Table 1. Examples of prediction problems that ATOM can address with goal functions other than job success

Applications areas (Goal functions)	**Predictors** (Characteristics of the individuals that influence these occurrences)
work motivation of handicapped people (intention to return to work)*	marital status, place of residence *(farmhouse, village, small town, big city)*, living conditions *(without conveniences, with some conveniences, with all conveniences)*, salary, total income, living in family *(yes, no)*, if living in family *(number of family members living together, number of earning family members living together)*, years being unemployed, education *(no finished education, elementary school, secondary school, college, university, PhD)*, age, gender etc.
employees' turnover	salary, total income, place of residence *(farmhouse, village, small town, big city)*, living conditions *(without conveniences, with some conveniences, with all conveniences)*, living in family *(yes, no)*, if living in family *(number of family members living together, number of earning family members living together)*, education *(no finished education, elementary school, secondary school, college, university, PhD)*, age, gender etc.
churn, attrition *(cancelling e.g., telephone, cable TV, insurance, journal, etc. subscriptions by customers)*	financial situation *(heavy debt, moderate debt, no debt, properties)*, salary, total income, place of residence *(farmhouse, village, small town, big city)*, education *(no finished education, elementary school, secondary school, college, university, PhD)*, age, gender etc.
default in payment *(a borrower stops making the required payments on debt to banks or insurance companies)*	financial situation *(heavy debt, moderate debt, no debt, properties)*, salary, total income, place of residence *(farmhouse, village, small town, big city)*, education *(no finished education, elementary school, secondary school, college, university, PhD)*, age, gender etc.
voting to a particular political party	to which party voted earlier, participation in public life, religiousness, place of residence *(farmhouse, village, small town, big city)*, education *(no finished education, elementary school, secondary school, college, university, PhD)*, age, gender etc.
getting a particular illness	other illnesses, smoking, alcohol consumption, eating habits, lifestyle, hereditary disease risks, BMI, age, gender etc.
need for replacing hip or knee prostheses	illnesses, lifestyle, daily body movements, targeted body exercises, BMI, age, gender etc.
subjective well-being (individual happiness index)	financial situation *(heavy debt, moderate debt, no debt, properties)*, salary, total income, religiousness, unemployment, living in family *(yes, no)*, participation in public life, place of residence *(farmhouse, village, small town, big city)*, education *(no finished education, elementary school, secondary school, college, university, PhD)*, age, gender etc.

Applications areas (Goal functions)	**Predictors** (Characteristics of the individuals that influence these occurrences)
infection or death of experimental animals in medical and pharmaceutical experiments**	antecedent treatments/medications/surgeries, age
yield of a particular crop in experimental soil parcels**	soil chemistry, daily sunny hours, fertility, use of organic/ *synthetic* fertilizers, soil moisture, irrigation rate, tillage etc.

Notes:

* This example is presented in more detail as the fifth case study in the last article of this special issue, titled *Illustrating real-life ATOM application case studies.*

** In these examples – unlike the earlier ones – the “individuals” are not even humans, but animals or soil parcels

A short prospective exposition of the content of the present special issue

Lajos Izsó: *The concept of an AI-based expert system (ATOM) for predicting job success* (this very article, at the same time also an issue editor’s introduction)

Bence Gergely & Szabolcs Takács: *ATOM – a flexible multi-method machine learning framework for predicting job success*
ATOM’s outstanding flexibility is primarily ensured by using expediently selected concurrent algorithms. This means that in ATOM, as opposed to the general practice of specifying a single model, several ML algorithms run in parallel. Thus, we can choose the solution that best suits the given situation. The main advantage of competitive algorithms is that they can adapt to the diversity of workforce selection. It is also adaptable to student datasets of variable size and quality, to expert evaluation, as well as to specific job characteristics and latent data generation processes. However, by increasing the flexibility of the procedure, we also increase the possibility of the so-called “overfitting”, which also means that the algorithm only learns the data itself, i.e., it will not – or only to a limited extent – be able to generalize and identify patterns. We solved this problem in ATOM with proper cross-validation.

Judit T. Kárász & Szabolcs Takács: *Use of open and closed items in automation of evaluation systems*
Can we leave out open-ended items during automatic processing without significant distortion? Answering this question was decisive for the development of ATOM. Involving more than 80,000 respondents, we tested the mass consequences of omitting open-ended items on the data of the National Assessment of Basic Competencies (NABC). Our test runs showed that during the continuous evaluations, we were able to show quite close correlation levels – over 0.95 – between the versions that included open-ended questions and those that did not.

Examination of the results at the category level revealed that typically there are relatively significant differences at the two ends of the measurement scale, which has consequences for the application of ATOM as well.

Máté Pusker, Bence Gergely & Szabolcs Takács: *ATOM's structure – employee and employer feedback, survey site*
As described earlier, the ATOM program package has the following three main sets of functions according to the three main user categories that typically occur: (1) employees' functionalities, (2) employers' functionalities, and (3) experts' functionalities. The specific particular functions of these sets of functions can be accessed from the ATOM opening screen, via the following four primary windows: *"Users"*, *"Questionnaires"*, *"Setup"*, and *"Campaigns"*. The article deals with a detailed description of these functionalities from a practical point of view.

Lajos Izsó, Blanka Berényi & Máté Pusker: *Jointly applying a work simulator and ATOM to prevent occupational accidents and MSD through workforce selection*
The primary goal of this article is to present a promising concept using a work simulator (like ErgoScope) and ATOM combined.

The essence of this approach is to predict candidates' propensity for MSD-type *(Musculoskeletal Disorder)* occupational diseases and for causing or suffering workplace accidents based on ErgoScope measurements as inputs to ATOM.

The purposeful combination of ErgoScope with ATOM can have a "synergistic" effect that reinforces each other's impacts, significantly reducing the likelihood of MSDs and workplace accidents. To put it simply, we propose to apply the appropriate outputs of ErgoScope as inputs to ATOM.

Lajos Izsó, Blanka Berényi & Szabolcs Takács: *Illustrating real-life ATOM application case studies*
In this article, five specific, real-life case studies are presented based on the results obtained with the help of experts' functionalities of ATOM. The employees' and employers' functionalities were not involved in these studies.

All the predictors and parameters of job success in these case studies were entered into ATOM as external files. For simplicity, reliability and uniformity reasons, parameters of job success were given on two-point (i.e., binary) scales, where 1 = "less likely to be successful in the job", 2 = "more likely to be successful in the job". For characterizing the overall categorization performance of ATOM, the ROC curves and the Precision-Recall curves were used. As opposed to assessing overall categorization performance based on all possible cutoff levels, it is also shown how particular local compromises – between sensitivity (recall), specificity, and precision – can be found, if necessary, by purposefully selecting cutoff levels.

In all the articles within this special thematic issue, there is double referencing. The internal references (citations), relating to this special issue, come first. Later, separately, the external references follow in the usual way.

Összefoglaló

Egy munkahelyi beválás előrejelzésére szolgáló MI-alapú szakértői rendszer (ATOM) koncepciója

Háttér és célkitűzések: Jelen cikk egyfelől az ebben a különszámban megjelenő – a munkahelyi beválás mesterséges intelligencia (MI) alkalmazásán alapuló előrejelzését ismertető – többi cikknek egy rövid, előretekintő ismertetését adja, másfelől pedig egy általunk kifejlesztett konkrét implementációt is bemutat vázlatosan.
Azon túlmenően, hogy a cikk szélesebb pespektívában ismerteti az MI alkalmazásának lehetőségeit és korlátait az emberierőforrás-menedzsment (EEM) különböző területein – mint a toborzás, munkaerő-kiválasztás, alkalmazás, képzés, teljesítmény nyomonkövető mérése és menedzselése, bérezés, munkaügyi viszonyok, munkahelyi biztonság- és egészségvédelem stb. –, a szöveg egyúttal ezen különszám szerkesztőjének előszava is.
Az EEM-területeket támogató jelenlegi MI-alkalmazások elsősorban a toborzásra korlátozódnak, a többi területeken a cégek még nagyrészt hagyományos módszereket használnak. Minthogy a gyakorlat azt mutatja, hogy a HR munkatársak rendszerint alulteljesítenek a munkaerő kiválasztása során, elsősorban erre a feladatra fejlesztettük ki az ATOM (Alkalmasság Tesztelési/Osztályozási Modul) nevű MI-alapú rendszerünket. Az ATOM a kiválasztáson túlmenően a toborzást is képes hatékonyan támogatni, és valamilyen mértékben még a munkahelyi biztonság- és egészségvédelmet is.
Az ATOM alapfeladata „megtanulni" az alkalmas prediktorok (a beválás előrejelzésére alkalmas változók) és a releváns beválási kritériumok közötti kapcsolatot az adott munkakörre. Az ATOM kiemelkedő hatékonyságot és rugalmasságot biztosító újszerű vonása, hogy a magjában sok tanuló algoritmus fut konkurens módon, és az ezek által produkált eredmények közül a rendszer mindig a legjobbat fogadja el..

Kulcsszavak: mesterséges intelligencia (MI), gépi tanulás, emberierőforrás-menedzsment (EEM), munkahelyi beválás, ATOM

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