Online Journal of Applied Knowledge Management

A Publication of the International Institute for Applied Knowledge Management

Volume 12, Issue 2, 2024

The potential of using artificial intelligence in developing individual human intelligence profiles

Maria Pietrzak, Warsaw School of Economics, Poland, maria.pietrzak@sgh.waw.pl

Ryszard Ząbkowski, Poland, r.zabkowski@gmail.com

Abstract

It seems that most educational systems nowadays are focused on just part of human intelligence (basically logical, mathematical, and lingual), which implies a lot of general assumptions and actions in the teaching process. As a result, many students are treated as untalented because their dominant intelligence is not the one valued in today's schools. This causes both frustration and educational problems, not to mention the fact that many great abilities are being wasted due to being undiscovered. This article aims to investigate the possibility of using Artificial Intelligence (AI) to define individual intelligence profiles, which can be used to outline personal development paths in line with the specific set of talents of every human being. Based on the literature review, the authors have identified a need for further qualitative research aimed at projecting a roadmap focused on discovering the complete personality profile of everyone with the use of AI and then creating the optimal development path for people to reach their full potential. This will be very advantageous for both individuals and the whole society. We kindly invite all the researchers interested in implementing AI in holistic talent diagnosis and development to contribute to a common, systematic, and interdisciplinary research project that would aim at taking full advantage of AI opportunities for individuals, specific communities, and the whole society.

Keywords: Artificial Intelligence (AI), individual potential, talent, personal development, educational system, teaching.

Introduction

The current perspective on public teaching is deeply grounded in many countries. It has its roots in the year 1900, when psychologist Alfred Binet responded to the request to create a tool for children at Parisian schools to identify learning problems and support them in their educational journey. The "tool" proposed by Binet, commonly known as the Intelligence Quotient (IQ) test, has since then become the major instrument used to estimate one's potential (Gardner, 2000).

The IQ test's problem is that it mainly values two kinds of human intelligence - the ones that are easy to estimate. These are mathematical-logical, and lingual intelligence. However, those two represent only a small part of human potential. Additional studies indicate that in the case of abilities and skills, different parts of the human brain participate in the final performance of every human being (Dubin, 2013). One of the examples here may be the reading process which uses both linguistic and nonlinguistic general auditory skills so children insensitive to spoken auditory units have more difficulties in reading (Anvari et al., 2002). On the other hand, there is growing evidence

DOI: https://doi.org/10.36965/OJAKM.2024.12(2)1-14
Accepting Editor: Meir Russ

that some extraordinarily talented people are very poor students which might be explained by the set of intelligence they have that is not directly addressed by school programs (Lakin & Wai, 2020). Other research suggests that achieving an outstanding performance is not a matter of any specific talent but a choice to work hard and attain admirable levels of advancement by practice (Colvin, 2010; Johnson et al., 2008; Kennedy, 2017; Syed, 2010).

Given that personal traits may be the most significant factor influencing one's achievement, research on talent discovery and development that focuses on the design of neural networks in education is growing (Cazares & Martin, 2018; Okewu et al., 2021). The importance of Artificial Intelligence (AI) in the teaching and learning process has been similarly growing (Holmes & Tuomi 2022; Zai et al., 2021) with a focus on finding the most appropriate and human-friendly use of AI in the education system since it is no longer possible to stop the development and AI application in education.

This research aims to investigate the possibility of using AI to define individual intelligence profiles which would be helpful to outline personal development paths in line with the specific set of talents of every human being. The authors' research goal is to establish foundations for designing easy but accurate tests that diagnose individuals' talent profiles with the use of AI systems. Moreover, the authors would like to summarize the research completed so far in order to invite other researchers and AI practitioners to join forces so that this can be applied on a large scale.

Based on the literature review, the authors aim to conduct qualitative research to propose a roadmap for discovering the complete talent profile of every person, using AI to create the optimal development path that will help individuals reach their full potential. The authors are aware of the complexity of the process, and the resource intensity, but the opportunity that AI presents for human development is important. The precise diagnosis of every individual's talent potential after just one well-prepared and organized test shall be very advantageous to both individuals and society as a whole. Given the increasing number of people feeling depressed due to their inability to develop in accordance with their real potential, this importance grows further (Friedrich, 2017; Wilson & Dumornay, 2022).

The paper will start with a short summary of the definitions and possible measures of human potential, focusing on the one used further in the paper. Then, cognitive education is to be explained. Following this, a description of how AI could be used in defining one's individual development path is given. The support and challenges around possible AI implementation in personal development are then stated to give a broader perspective. Finally, the authors depict the research limitations and outline further research steps.

Defining and Measuring Human Potential

Multiple Intelligence

There are various definitions of intelligence (Strelau, 2023). In this paper, the authors adopted the definition presented by Gardner, named the Theory of Multiple Intelligence (Gardner, 1989). Gardner 'proposed the existence of several relatively autonomous human intelligence' and 'defined intelligence as the capacity to solve problems or to fashion products that are valued in

DOI: https://doi.org/10.36965/OJAKM.2024.12(2)1-14

Accepting Editor: Meir Russ

one or more cultural settings and detailed a set of criteria for what counts as human intelligence'. With this in mind, Gardner defined at first seven and then eight major types of intelligence categories which are:

- Mathematical-logical (typically held by scientists and mathematicians)
- Linguistic (poet, journalist)
- Musical (composer, singer, violinist)
- Spatial (architects, navigators, and sculptors)
- Bodily-kinesthetic (dancer, athlete)
- Interpersonal (therapist, salesman)
- Intrapersonal (people with accurate self-knowledge)
- Natural scientific (forester, vet)

However, many people have a very unique set of those types of intelligence, with 2 or 3 dominating but not being extraordinarily developed, which makes (for example) the choice of the profession not so obvious and easy (Gardner, 1989, pp. 58-63).

Since intelligence is typically defined as a set of abilities, it is worthwhile specifying the areas of their potential occurrence. Strelau (2023) identified potential capacities, actual abilities, and the real level of their performance. In the design of AI systems analyzing tests and making predictions, it is crucial to distinguish between the intelligence presented by the person and the level derived from the tests showing rather the potential which is not necessarily fully realized in many cases (Duckworth 2006; Sternberg, 1997, 2009).

In summary, the elimination of the gray area between abilities, capacities, and actual performance becomes an area of educational intervention. Talent development is, therefore, an extremely important action, especially when considering the holistic development of the individual.

Gardner with his scientific team proves in his multiannual research that “an especially prepared encounter of a certain material, device or people may help every child to find their own calling” (Gardner, 2000, p. 56). Leading on from that it can be assumed that if we invest in designing a comprehensive tool to enable every person to reach their full potential, not only the happiness and well-being of individuals rise, but also the whole society shall benefit from reducing productivity losses and mental health disorders to name just a few possible side effects of poor talent diagnosis and development.

Cognitive Education

The idea of cognitive education is to get to know a person in such a way as to recognize specific potential much earlier than they themselves will be able to do so. This will help young people steer their own individual career paths and develop their talents before they get frustrated by selecting areas that are not their natural predisposition. Thus, enabling the optimal development of their talents and intelligence. One of the authors of this paper once had an opportunity to design a career center. He suggested placing small mirrors on the wall and a large inscription: 'I see myself as...' - under the mirrors and placed names of various professions: manager, supervisor, programmer, cashier. That enabled people to see themselves in a specific role and so examine which of them

DOI: https://doi.org/10.36965/OJAKM.2024.12(2)1-14
Accepting Editor: Meir Russ

suits them best, corresponding the most with their own unique temperament, personality, character, and set of talents. Perhaps, something of that kind could be used in the AI-designed talent test.

Learning Path Tailored to Individual Needs and Abilities

Individual and Group-Focused Model

An individual attitude towards education stems from ancient Greece. Socrates is said to be known for teaching through engaging in interactive one-to-one dialogues. Nowadays, the universality of education makes teaching in such a style economically impractical for most societies. The current educational system has shifted from an individual-focused teacher attention model to a group-focused model. Innovations in process optimization and knowledge management highlight the need for adjustments to this model (Russ, 2021). Various alternative education solutions have emerged in this context, including homeschooling (Jeynes, 2016). Despite this, changing the overall trend is far from immediate, not only because of the cost of such a shift but also due to strong counterarguments raised against alternative forms for the current dominant group-focused teaching model. Firstly, it is assumed that the teaching process should be conducted following common standards regarding the place, time, and strict scientific instructions. Those assumptions stem from public efforts to ensure the same learning opportunities and the same qualities of instructions, which increases the risk of learning being an imposed process, resulting in gaining predominantly superficial knowledge. Secondly, it is important to note that the process of individualization and personalization of teaching often relies on the commitment and self-discipline of the student, with a limited role and impact on the teacher (Martens et al., 2007; Skarpenes & Hidle, 2024). This approach carries the risk of low-commitment mentoring, unlike responsible tutoring. The teaching perspective in which every individual is treated uniquely may however gain popularity in the future, due to the constant development of neural networks. The authors' hopes are high, which makes it worthwhile carrying out an in-depth analysis in that field.

The Two Sigma Problem

There is a lot of evidence showing that the search for more accurate and tailor-made teaching is reasonable and worthy of investment (e.g. Karpenko et al., 2019). Numerous researchers have proved in their papers that if we aim for more effective learning, more individualization is needed (Cheng, 2005; Uglev, 2014). The Two Sigma problem remains a significant issue in education debates (Bloom, 1984). Bloom has empirically demonstrated the difference between teaching a group of 30 students and individualized tutoring at a 1:1 ratio. In the personalized learning process, exam results improve by 50% compared to group teaching, and the grade spread is significantly reduced. Leading on from that, Bloom proposed a ‘mastery learning’ strategy attempting to bridge the results’ gap improving group performance and approaching optimal values by 30% (Bloom, 1984).

Mastery Learning Techniques

Since then, mastery learning techniques have been dynamically evolving (Guskey, 2007). Such techniques primarily rely on initial assessment, test modeling, rehearsal techniques, feedback, correction, enrichment, and formative evaluation (Guskey, 2022). The cognitive approach remains a crucial axis for improving the situation and achieving better teaching outcomes. The adopted

DOI: https://doi.org/10.36965/OJAKM.2024.12(2)1-14

Accepting Editor: Meir Russ

mastery learning strategy is based on regular feedback, individual correction of elements slowing down the learning process (if needed), planning, and adjusting instruction (Winget & Persky, 2022). These are also significant components of 1:1 tutoring. The tutor's attention is focused on cognitive tests during the teaching time in real life. Even while imparting knowledge, they can interpret non-verbal signals sent by their students, such as facial expressions.

Something worth exploring is the initial assessment. Representatives of the machine learning trend seem to attach less importance to this element, however in cognitive and positive psychology, this diagnosis has taken its proper significant place (Ruch et al., 2014). In the future, recognizing an individual's intelligence type shall provide us with reliable empirical foundations for modeling necessary guidebooks and assessment tests.

Cognitive Diagnostic Assessment

Discovering and defining one's specific set of abilities allows people to determine an individual's cognitive strengths and weaknesses. Leading on from that, Cognitive Diagnostic Assessment (CDA) is a set of techniques that enables the effective creation of cognitive tests (Leighton, 2007). These methods provide an initial diagnostic-level assessment, mainly qualitative rather than descriptive in nature, but maximizing the significance of feedback. These tests are evaluated with the use of Cognitive Diagnostic Models (CDM), which focus first on analyzing, and then on extracting information from both CDA and non-diagnostic tests and reporting. Especially in terms of providing CDA can be considered a step forward in terms of providing feedback, a goal that educational measurement has always sought to achieve. Despite improving the quality of teaching, the complexity of these methods and their relative novelty mean that they have not yet found a proper place in educational diagnostics. This objective can only be met by operationalizing and applying CDA in both classroom assessments and large-scale tests (Javidanmehr & Sarab, 2017). This requires a deep structural understanding of the theoretical foundations of CDA and CDM. There is no doubt that percentage test scores can lead to different conclusions. That's why using precise methods is obligatory to minimize prediction errors. Diagnosis of multiple intelligences should focus on a qualitative cognitive analysis of the results. Only then can we draw proper conclusions and make optimal predictions regarding the student's career path based on their potential.

CDA serves as the first step here. Proposed by Qi Liu, Neural Cognitive Diagnostic (Neural CD) as a research framework is a non-trivial proposition to solve the problem of input-data heterogeneity. It considers the non-linear interactions between different parts of the human brain that influence the way every person acts and reacts to different tasks and situations (Wang & Liu et al., 2020). Notwithstanding the novelty and added value of the solution proposed in the Neural CD framework, many complex issues still raise questions. Some of the most important are: how to optimally utilize the obtained data (data mining and recursive method); and how to create sophisticated tests allowing for the extraction of the maximum amount of information without any kind of violation of law and personal rights. The demand for improving data collection and processing aims to make education management and service delivery more equitable, connected, and personalized. It is essential to consider also the perspective and the opportunities of lifelong learning (Beijing Consensus, 2019).

DOI: https://doi.org/10.36965/OJAKM.2024.12(2)1-14

Accepting Editor: Meir Russ

AI is reshaping the job market, so future skills will also reference AI. Nevertheless, it must be underlined that artificial intelligence is not a prosthesis for our own brains. AI's purpose is to significantly assist us in developing various scientific fields and so make human development still more advanced. The paper authors emphasize that collaboration with AI (of any kind) should not deprive us of lingual and mathematical skills which are indispensable for efficient management and collaboration with these systems. Therefore, it seems that the main feature that will determine the quality of our cooperation and collaboration with machines is a kind of specific partnership (Dong et al., 2020; Fahimirad, & Kotamjani, 2018).

AI in Talent Investigation

When using AI for versatile talent investigation, one should remember that AI has changed the nature of work through dynamic processes and reconfigured power relations together with social dynamics. There are two main perspectives on the coexistence of humans and machines at work: 1) human-robot collaboration, and 2) worker-centered technology design. The second seems to be weaker, as thinking about labor has mostly an economic background. The third solution emerging, which has the potential to become a leading approach, is the Human-Machine Partnership (HMP) (Miniankou & Puptsau, 2024). This collaboration requires consideration of such topics as worker psychological training, inner acceptance of work with robots, new work distribution, and redefinition of certain tasks. In general, it entails rethinking our approach to working with robots. There was a time when humans were separated from robots, and now multisensory machines have become partners with humans. In this context, considering robot rights appears important.

The natural course of development involves the creation of AI systems based on Cognitive Diagnostic Assessment trained on data extracted using Cognitive Diagnostic Models (Bolt, 2007; Deonovic et al., 2019). Such a system could represent a significant step forward in the field of cognitive diagnostic scalability. For projects, data analysis, and modeling, it may be the case, for example, that people lose some inborn capabilities when they are not used by a certain age. Expectedly, more integrated AI systems will be needed to take full advantage of AI possibilities in talent diagnosis. Each subsequent model will be trained on data from the previous model. This model would potentially be able to tailor tests and educational materials to the specific needs of the student. Operating on the principle that interconnected vessels allow for optimal utilization of the system, we are not dealing with one large system but with a group of smaller knowledge models. The resulting supporting profile shall be an incredible aid for teachers. The idea of collaboration between advanced AI systems and humans seems to fit the most for this purpose. However, achieving this goal requires further research in the integration of CDA and CDMs with AI to discover hidden patterns in data for comprehensive knowledge management. These patterns emerge in data mining processes and will be crucial for the future of education. The process has become dynamic and reflective. Without working with big data sets, the objectives of the paper will not be achieved. It is crucial to observe the wider picture but not lose sight of the individual. That approach can be called 'watching through the telescope and microscope at the same time'. It involves understanding global trends and recognizing the complexity of an individual, along with their unique talents and intelligence.

DOI: https://doi.org/10.36965/OJAKM.2024.12(2)1-14

Accepting Editor: Meir Russ

Discussion

Pros and Cons of AI in Talent Diagnosis

In general, most of the current AI systems designed for education (like the systems Walter or Khanmigo) diagnose needs and create a student profile based on prompts (Walter, 2024). As for now, due to insufficient versatile and well-prepared data inserted into the systems, this results in a very superficial understanding. Aside from the structural disabilities of AI systems (e.g. hallucinations), more reasons make them so far, rather poor cognitive teaching methods. An important matter, for example, is the validation and adjustment system, which is currently temporary and short-sighted. The lack of a broad perspective in this case poses a significant risk, as it refers to a delicate matter of a person's future and career. That is just another reason why the idea of a machine being the sole tutor remains inappropriate if not unacceptable.

The concept of Sal Khan advocating universal access to education and the development of online tools seems to compel a conciliatory approach that gives directions for future research (Dijksman & Khan, 2011). But, if that is considered a global option for equalizing educational opportunities, everyone should be aware of the challenges. One of the greatest is that when the student gets solely the diagnosis of the machine, he or she can feel confused with the diagnosis. The fact that the supplier of the system imposes the paths of development carries the risk of fragmented education. That is why the authors suggest redefining the need to recognize cognitive human career paths with the application of AI systems. It could bring a new perspective and opportunities in the dynamically changing labor market.

Most current computer systems appear to focus primarily on delivering potential educational content without real cognitive diagnostic accuracy. Although different computer systems are already used in educational paths: two-dimensions (2D), three-dimensions (3D) applications, Virtual Reality, web-based educational apps, Udemy, and other video training platforms (Koedinger & Corbett, 2006), they have not yet solved the mentioned above Two Sigma problem globally.

While creating talent diagnostic systems based on AI, one should not lose sight of the European local law (AI Act, 2022). It precisely outlines the framework for such mechanisms. The legislator categorizes mechanisms related to education as high-risk and describes them as follows: Education and vocational training: (1) AI systems intended to be used to determine access or admission or to assign natural persons to educational and vocational training institutions at all levels; (2) AI systems intended to be used to evaluate learning outcomes, including when those outcomes are used to steer the learning process of natural persons in educational and vocational training institutions at all levels; (2a) AI systems intended to be used to assess the appropriate level of education that individual will receive or will be able to access, in the context of/within education and vocational training institution; (2b) AI systems intended to be used for monitoring and detecting prohibited behavior of students during tests in the context of/within education and vocational training institutions. (AI ACT, Annex III, 2023).

When framing working talent diagnostic systems, one has to be aware of the fact that they have significantly higher security requirements. Legislators highlight several elements aimed at preventing abuses in this matter. These include: Compliance with the Requirements, Risk

Management System, Data and Data Governance, Technical Documentation, Record-Keeping, Transparency and Provision of Information to Deployers, Human Oversight, Accuracy, Robustness, and Cybersecurity. Imposing such strict requirements on companies creating such systems carries the risk of either a lack of commercial implementation or functional deficits in those systems. On the other hand, however, these limitations allow for maintaining the necessary accuracy in terms of broadly understood security (Elliott & Soifer, 2022; Habbal & Abuzaraida 2024).

Table 1. Opportunities and Threats of AI Cognitive Diagnostics

AI Cognitive Diagnostics			
Opportunities		**Threats**	
Precision *A very precise and versatile picture of every individual potential and so the most advantageous career path*	Why? Thanks to engagement in the tool design of multidisciplinary researchers and the significant amount of data	*Data Privacy* *A double threat of both data privacy violation and uncontrolled substitution of data.*	Why? Due to the major importance and scale of the project, highly valuable data is gathered which raises the interest of hackers and other criminals
Individualization *A unique talent profile for every person, 100 % specific for the concrete person*	Why? Thanks to a huge amount of versatile data considering many individual features (also living conditions) and specifics	*Bias* *Possible misassessment of the individual potential and so wrong conclusions concerning possible development paths*	Why? due to specific interpretation of the data by the algorithms used in the system and/or failures in the preliminary assumptions
Data mining *Many options for interesting research based on the data collected in the system*	Why? Thanks to huge amounts of versatile data	*Faulty cooperation between people and AI systems* *False courses of action based on assumptions that are incorrect to a high extent*	Why? Some people trust algorithms excessively, some mistrust them totally
Interdisciplinary findings *A great option for multidisciplinary research teams*	Why? Thanks to the engagement in the tool design of multidisciplinary researchers.	*Ineffectiveness* *Poor outcomes despite a high number of different resources invested (time, money, etc.)*	Why? Due to overcomplexity of the system

The summary of opportunities and threats in AI Cognitive Diagnostics identified by the authors of the article based on a literature review (Adeshola & Adepoju, 2023; Kenthapadi, Lakkaraju & Rajani, 2023; Piorkowski, Hind & Richards, 2022) is presented in Table 1.

Basic Assumptions

It must be underlined that to take full advantage of the opportunities of AI cognitive diagnostics and gain a comprehensive understanding of individuals' potential and possible developmental paths, three basic assumptions should undoubtedly be met:

- The AI system used in the diagnostic process is fed with a significant amount of valid data (Kwon et al., 2023)
- Both the feeding and training process of AI systems as well as verifying the accuracy of the evaluation, theories, and tools used in the diagnostic process is constant (Bratteteig & Verne, 2018)
- The diagnostic cognitive tool is simple but complete (meeting all the demands set by the interdisciplinary designers of the cognitive diagnostic tool)

Further Research and Development Plan

Being mindful of all necessary assumptions, together with the possible opportunities and threats of the AI application in diagnosing individual potential and proposing optimal development paths, it is important to state clearly how the authors plan the research steps and the development of the diagnostic tool.

1. Design of a comprehensive but simple diagnostic tool supported by AI systems through a multidisciplinary team led by cognitive scientists.
2. Data collection in a way suggested by the designers of the diagnostic tool.
3. Inserting the collected data into AI systems.
4. Training of AI systems aimed at delivering precise talent profiles and suggestions of optimal development paths corresponding precisely to individual profiles.
5. Constant data collection and training of AI systems connected to constant verification of project assumptions and frameworks based on an ever-growing dataset aimed at improving the quality of results.
6. Parallel multidisciplinary research projects concerning such aspects as understanding how certain types of talents coexist and influence one's preferences of favorite activities and jobs, or how lifestyle influences the ability to fulfill one's potential.

Conclusion

AI is not a prosthesis for our own brains but can be very helpful in designing complex educational models aimed at evaluating the individual potential of every human being and their most adequate development path. Determining the potential talent set of children can be of significant value not only for cognitive educators but also for parents and young people alike. Among others, the AI Cognitive Diagnosis shall help to reduce the gap between the potential of every human being and the actual underperformance of people in real life with regard to projections and expectations based on available IQ tests. What is more, it should also help to solve many problems such as prevailing frustration among people dissatisfied with their professional career paths quite often mismatched with their natural potential. However, to make the system of cognitive education work effectively, certain basic assumptions must be considered. These are, inter alia, a sufficiently large data system incorporating interactions between human synapsis and complex interdependencies

DOI: https://doi.org/10.36965/OJAKM.2024.12(2)1-14

Accepting Editor: Meir Russ

between specific abilities, disorders, and other factors; proper control of the system to avoid privacy violation; and cooperation between people and machines, in which appropriate attitude and authentic engagement of every person in frame working the system. Above all, however, the careful design of the diagnostic tool with a precise outline of the type and quality of data is paramount. This tool should be designed by a multidisciplinary team consisting of cognitive scientists, neurologists, psychologists, and educators, but also ethnologists, anthropologists, and linguists or mathematicians.

Limitations

There are various limitations of the research completed to date that should be acknowledged:

- The authors are novices in the field of AI and talent development and so their findings may be superficial for advanced researchers in both fields.
- The literature has not been systematically reviewed. The authors have chosen purposely those available papers which they considered important and insightful.
- Both AI and talent diagnosis and development are vast scientific fields in which there is much ambiguity making it difficult to reach conclusions that can be replicable, falsifiable and ready to be implemented in practice.

Invitation for Collaboration

The authors of the article are aware that the projected process of designing and implementing the diagnostic tool shall be demanding. As for now a basic literature overview has been completed and the next step should be to develop a research roadmap based on design thinking and other qualitative methods. By publishing this article, the authors kindly invite other scientists but also practitioners to join the project and make it applicable. Due to high hopes concerning the projected outcomes, the process will certainly be resource intensive, but it seems that the true happiness of people resulting from their proper talent diagnosis and further development seems not only fascinating but also worthwhile.

References

Adeshola, I., & Adepoju, A. P. (2023). The opportunities and challenges of ChatGPT in education. *Interactive Learning Environments,* 1-14. http://dx.doi.org/10.1080/10494820.2023.2253858

AI Act Annex III (2023). https://artificialintelligenceact.eu/annex/3/

AI Act (2023). https://artificialintelligenceact.eu/ai-act-explorer/

Anvari, S. H., Trainor, L. J., Woodside, J., & Levy, B. A. (2002). Relations among musical skills, phonological processing, and early reading ability in preschool children. *Journal of Experimental Child Psychology, 83*(2), 111-130. https://www.sciencedirect.com/science/article/abs/pii/S0022096502001248

Bloom, B. S. (1984), The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutorial. *Education Researcher, 13*(6), 4-16. https://web.mit.edu/5.95/readings/bloom-two-sigma.pdf

Bolt, D. (2007). The present and future of IRT-based cognitive diagnostic models (ICDMs) and related methods. *Journal of Educational Measurement, 44*(4), 377-383.

Bratteteig, T., & Verne, G. (2018, August). Does AI make PD obsolete? exploring challenges from artificial intelligence to participatory design. *Proceedings of the 15th Participatory Design Conference: Short Papers, Situated Actions, Workshops and Tutorial-Volume 2* (pp. 1-5). http://dx.doi.org/10.1145/3210604.3210646

Cazarez, R. L. U., & Martin, C. L. (2018). Neural networks for predicting student performance in online education. *IEEE Latin America Transactions, 16*(7), 2053-2060. http://dx.doi.org/10.1109/TLA.2018.8447376

Colvin, G. (2010). *Talent is overrated: What really separates world-class performers from everybody else?* Penguin.

Cheng, Y. C. (2005). New paradigm for education reforms: Globalization, localization, and individualization. *New Paradigm for Re-engineering Education: Globalization, Localization and Individualization*, 19-44. https://doi.org/10.1007/1-4020-3620-5_2

Deonovic, B., Chopade, P., Yudelson, M., de la Torre, J., & von Davier, A. A. (2019). Application of cognitive diagnostic models to learning and assessment systems. *Handbook of diagnostic classification models: models and model extensions, applications, software packages*, 437-460.

Dijksman, J. A., & Khan, S. (2011, March). Khan Academy: The world's free virtual school. *APS March Meeting Abstracts,* A14-006.

Dong, Y., Hou, J., Zhang, N., & Zhang, M. (2020). Research on how human intelligence, consciousness, and cognitive computing affect the development of artificial intelligence. *Complexity, 2020*(1). https://onlinelibrary.wiley.com/doi/full/10.1155/2020/1680845

Duckworth, A. L. (2006). *Intelligence is not enough: Non-IQ predictors of achievement*. University of Pennsylvania.

Dubin, M. W. (2013). *How the brain works*. John Wiley & Sons.

Fahimirad, M., & Kotamjani, S. S. (2018). A review on application of artificial intelligence in teaching and learning in educational contexts. *International Journal of Learning and Development, 8*(4), 106-118. http://dx.doi.org/10.5296/ijld.v8i4.14057

Friedrich, M. J. (2017). Depression is the leading cause of disability around the world. *Jama, 317*(15), 1517-1517. https://doi.org/10.1001/jama.2017.3826

Guskey, T. R. (2007). Closing achievement gaps: Revisiting Benjamin S. Bloom's "Learning for Mastery". *Journal of Advanced Academics, 19*(1), 8-31.

Guskey, T. R. (2022). *Implementing mastery learning*. Thousand Oaks: Corwin Press.

Gardner, H., & Hatch, T. (1989). Educational implications of the theory of multiple intelligences. *Educational Researcher, 18*(8), 4-10.

Gardner, H. (2000). *Intelligence reframed: Multiple intelligences for the 21st century*. Hachette UK.

Habbal, A., Ali, M. K., & Abuzaraida, M. A. (2024). Artificial intelligence trust, risk and security management (AI trism): Frameworks, applications, challenges and future research directions. *Expert Systems with Applications, 240*, 122442. https://doi.org/10.1016/j.eswa.2023.122442

Holmes, W. & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education, 57*(4), 542-570. https://doi.org/10.1111/ejed.12533

Javidanmehr, Z. & Sarab, M. R. A. (2017). Cognitive diagnostic assessment: Issues and considerations. *International Journal of Language Testing, 7*(2), 73-98. https://files.eric.ed.gov/fulltext/EJ1299439.pdf

Jeynes, W. H. (2016). Homeschooling: The ultimate personalized environment. *Handbook on personalized learning for states, districts, and schools*, 99-113.

Johnson, M. B., Castillo, Y., Sacks, D. N., Cavazos Jr, J., Edmonds, W. A., & Tenenbaum, G. (2008). "Hard Work Beats Talent until Talent Decides to Work Hard": Coaches' Perspectives regarding Differentiating Elite and Non-Elite Swimmers. International *Journal of Sports Science & Coaching, 3*(3), 417-430.

Karpenko, O. M., Lukyanova, A. V., Bugai, V. V., & Shchedrova, I. A. (2019). Individualization of learning: An investigation on educational technologies. *Journal of History Culture and Art Research, 8*(3), 81-90. http://dx.doi.org/10.7596/taksad.v8i3.2243

Kenthapadi, K., Lakkaraju, H., & Rajani, N. (2023, August). Generative ai meets responsible ai: Practical challenges and opportunities. *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 5805-5806. https://doi.org/10.1145/3580305.3599557

Koedinger, K. R. & Corbett, A. (2006). Cognitive tutors: Technology bringing learning sciences to the classroom. In R. K. Sawyer (Ed.), *The Cambridge handbook of: The learning sciences* (pp. 61–77). Cambridge University Press.

Kwon, Y., Han, J., Cho, Y. P., Kim, J., Chung, J., Choi, J., ... & Choi, M. (2023, February). Chiplet heterogeneous-integration AI processor. *Proceedings of the 2023 International Conference on Electronics, Information, and Communication* (ICEIC) (pp. 1-2). IEEE.

Lakin, J. M. & Wai, J. (2020). Spatially gifted, academically inconvenienced: Spatially talented students experience less academic engagement and more behavioural issues than other talented students. *British Journal of Educational Psychology, 90*(4), 1015-1038. http://dx.doi.org/10.1111/bjep.12343

Leighton, J. (2007). *Cognitive diagnostic assessment for education: Theory and applications*. Cambridge University Press.

Liu, Q. (2022). *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence.* Viena. https://www.ijcai.org/proceedings/2022/

Martens, R., Bastiaens, T., & Kirschner, P. A. (2007). New learning design in distance education: The impact on student perception and motivation. *Distance Education, 28*(1), 81-93. https://doi.org/10.1080/01587910701305327

Miniankou, R. & Puptsau, A. (2024). Artificial intelligence as a tool for human-machine partnership in the educational process. *Lecture Notes in Networks and Systems book series*, 913.

Okewu, E., Adewole, P., Misra, S., Maskeliunas, R., & Damasevicius, R. (2021). Artificial neural networks for educational data mining in higher education: A systematic literature review. *Applied Artificial Intelligence, 35*(13), 983-1021. https://doi.org/10.1080/08839514.2021.1922847

Ruch, W., Martínez-Martí, M. L., Proyer, R. T., & Harzer, C. (2014). The character strengths rating form (CSRF): Development and initial assessment of a 24-item rating scale to assess character strengths. *Personality and Individual Differences, 68*, 53-58. https://doi.org/10.1016/j.paid.2014.03.042

Russ, M. (2021). Knowledge management for sustainable development in the era of continuously accelerating technological revolutions: A framework and models. *Sustainability, 13*(6), 3353. http://dx.doi.org/10.3390/su13063353

Skarpenes, O., & Hidle, K. M. W. (2024). The clash of cultures: Individualization and standardization in education. *Policy Futures in Education*, 14782103241226526. https://doi.org/10.1177/14782103241226526

Sternberg, R. J. (1997). Managerial intelligence: Why IQ isn't enough. *Journal of Management, 23*(3), 475-493.

Sternberg, R. J. (2009). Academic intelligence is not enough WICS: An expended model for effective practice in school and later in life. *Innovations in Educational Psychology, 403*, 1-2.

Strelau, J. (2023). *Psychologia. Podręcznik akademicki*, Gdańskie wydawnictwo psychologiczne.

Syed, M. (2011). Bounce: the myth of talent and the power of practice. *(No Title).*

Uglev, V. (2014). Implementation of decision-making methods in intelligent automated educational system focused on complete individualization in learning. *AASRI Procedia, 6*, 66-72. https://doi.org/10.1016/j.aasri.2014.05.010

Wang, F., Liu, Q., Chen, E., Huang, Z., Chen, Y., Yin, Y., ... & Wang, S. (2020). Neural cognitive diagnosis for intelligent education systems. *Proceedings of the AAAI Conference on Artificial Intelligence*, *34*(04), 6153-6161. https://doi.org/10.1609/aaai.v34i04.6080

Wilson, S., & Dumornay, N. M. (2022). Rising rates of adolescent depression in the United States: Challenges and opportunities in the 2020s. *Journal of Adolescent Health, 70*(3), 354-355.

Winget, M., Persky, A. M. A. (2022). Practical review of mastery learning. *American Journal of Pharmaceutical Education*. https://doi.org/10.5688/ajpe8906

Winner, E. (1998). Uncommon talents: gifted children, prodigies and savants-often assumed to be well adjusted and easy to teach, gifted children and prodigies are generally out of step with their peers and can. *Scientific American*, *278*(4), 32-37.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity, 2021*, 1-18. https://doi.org/10.1155/2021/8812542

Authors Biographies

Maria Pietrzak, Ph.D., assistant professor in the Institute of Management at Warsaw School of Economics, Poland, her scientific interests are: talent discovery and development, leadership, business ethics, and effective communication. She is engaging in the popularization of science among society as well as multidisciplinary research focused on improving the quality of life of individuals and nations.

Ryszard Ząbkowski, MA, Computer Science teacher, his scientific interests are AI theory and models, cognitive psychology, teaching, cognitive interdisciplinary science, and AI popularization among society.