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# METHODS AND TECHNIQUES FOR ENHANCING THE EDUCATION SYSTEM THROUGH THE USE OF NEURAL NETWORKS

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***Abstract:*** *During the pandemic context, there has been a massive migration towards new forms of hybrid and online teaching, and education has faced new and substantial challenges. With the proliferation of new communication technologies, the issue of maintaining an educational dialogue among the members of the three major generations involved in the educational process - namely, Generation X, Generation Y, and Generation Z - while keeping them up to date with all the new discoveries, has emerged. Identifying communication methods across these generations and the ability to convey and evaluate their knowledge have become subjects of research. Our research focuses on establishing a correlation between accepted, preferred, and used learning methods and the current generations engaged in the educational process, with the challenge of creating a viable model. In this regard, we intend to leverage artificial intelligence and the capacity of neural networks to develop a predictive system capable of determining and suggesting personalized learning methods for each student.*
***Key words:*** *education, transition, digitization, neural networks.*

## 1. INTRODUCTION

The period corresponding to the pandemic caused by the "COVID-19" virus has brought about significant changes within the global educational system. The implications of this phenomenon are complex, as it has influenced both the teaching and learning methods and the physical and mental health of participants in this process, including students and teachers. Furthermore, it has exacerbated existing educational inequalities [1].

Due to isolation and school closures, the transition to online education has been accelerated, leading to an implicit need for adaptation by teachers, students, and tutors to new teaching and learning methods. In some cases, this transition has had a negative impact, given the lack of preparation, limited access to the internet, as well as the absence of necessary equipment and technological means that have become a necessity. The pandemic has also prompted a reevaluation of how education should be implemented; in some cases, elements of online education have been seen as beneficial, such as flexibility and the opportunity to learn at one's own pace. In this regard, the pandemic can be viewed as a catalyst for educational transformation and development [2].

Educational inequalities have also been exacerbated by this pandemic. Students from disadvantaged backgrounds often had limited access to the resources necessary for distance learning, such as digital tools, technologies, and internet access. This issue has led to an increase in the educational gap between students from privileged backgrounds and those from disadvantaged backgrounds [3].

The global crisis generated by the COVID-19 pandemic has significantly impacted the mental health of both students and teachers. School closures and the transition to remote education have increased anxiety and stress levels [4].

The pandemic caused by the COVID-19 virus has compelled several educational institutions to adopt online or even hybrid teaching methods. Rushing into distance learning is not equivalent to well-planned and effectively implemented

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online courses. Communication can be hindered by the lack of planning and adequate resources [5].

To mitigate these problems, some educational institutions, communities, and governments have implemented a series of progressive measures. These include distributing digital devices and facilitating internet services for students from disadvantaged backgrounds, providing online mental health services, and developing hybrid instructional strategies to adapt to various learning scenarios [6].

During the pandemic period, communication through digital platforms and applications has become exceptionally important, even crucial. It has been observed that using interactive digital tools can enhance participant engagement (in this case, students) and consequently improve communication effectiveness [7].

Furthermore, developments in technology and artificial intelligence open new directions for communication between students and teachers. Adaptive learning technology, powered by AI, can effectively contribute to customizing communication means, the communication process itself, and the requirements needed to fulfill individual participants' needs in this process [8].

Effective communication also involves addressing social and emotional aspects, not just the transmission of knowledge. Therefore, the development of socio-emotional skills can enhance communication and relationships in the classroom. In this context, nuanced communication formed between students and teachers is influenced by various factors, including online and hybrid instruction, communication applications, technological tools, artificial intelligence in education, social and emotional education. These factors can significantly impact the efficiency of communication in modern education [9].

Additionally, personalized learning has been discussed, implying that personalized communication can enhance and streamline the educational system when focused on interventions based on a growth mindset that can improve academic achievements [10].

In this regard, because certain aspects of mental health can influence communication and furthermore, academic stress can entail a general negative impact on the mental health of students and thus directly on their ability to communicate with teachers effectively [11], it is imperative that the approach to cultural diversity and inclusion can have a significant impact on effective communication. A potential response is provided by culturally responsive teaching, which represents a valid and potent approach with the capacity to enhance students' academic achievements [12].

The traditional standardized assessment of communication between teachers and students has often proven ineffective during this transitional period. This is because classic standardized evaluations frequently fail to reflect students' true understanding and competencies, leading to communication that is largely inefficient in addressing students' progress and needs [13].

On the other hand, personalized and differentiated assessment is becoming increasingly important in education today. It has been observed that teaching and learning systems geared toward personalized models can aid in improving academic achievements by continuously adapting the educational system to individual student needs and societal demands [14].

In this context, project-based learning has been explored, offering real opportunities for active engagement, and demonstrating its effectiveness in online environments. The benefits of project-based learning have been discussed and analyzed, with the hypothesis of increased student involvement and the potential to test and apply knowledge in real-world contexts [15].

In the case of project-based learning, the cooperative and active approach gains appreciation from both teachers and students. This represents a system in which certain students collaborate to achieve common goals, yielding several benefits, including improved subject understanding and the promotion of social skills for participants [16].

Moreover, placing the student at the center of the future educational process has proven highly effective. Student-centered learning has become essential for fostering creative and critical competencies [17]. Furthermore, due to the rapid development of technology, the idea of using predictive systems with the aid of artificial intelligence has been proposed, specifically through the involvement of neural networks. Neural networks are known for their ability to recognize and learn patterns from datasets. Thus, when presented with a dataset describing human behaviors in various situations, a neural network can be trained on this data to make predictions about similar situations in the future [18].

## 2. INFORMATION

Neural networks are comprised of flexible and powerful mathematical models, developed using artificial neurons that possess the ability to extract, process, and represent information from specific data. They are integrated into various processes such as natural language processing, object recognition, automatic translation, robotics, applications, games, and many more [19].

The outputs generated by neural networks are directly proportional to the accuracy of the input data and the trained models used in this process. The input dataset serves as a foundational establishment from which these networks extrapolate information. They then proceed to learn and internalize these patterns, classify them, and eventually take decisive or predictive actions on new emerging patterns [20].

An application that utilizes neural network systems is “Neuroshell”, which stands as a viable option due to its user interface and computational power. It can run on typical computer models using specific indicators [21] that later form the basis of a computational problem. The neural network then generates tests based on learning algorithms [22], employs the obtained data to train a model, learns to identify patterns and relationships within the training data [23]. After the respective model has passed the validation stage, it ultimately proposes predictors that form the basis for creating certain scenarios [24].

Precisely due to these considerations, we have chosen the “Neuroshell” application because we’ve aimed for a user-friendly application with considerable computational power. This choice aims to synthesize and train the involved data to establish a correlation between the accepted, preferred, and used learning styles (classic/reading-writing, auditory, visual, and kinesthetic) and the current generations in the educational process, namely Generation X, Generation Y, and Generation Z.

In the educational domain, perceiving and understanding the differences among individuals in learning approaches has become increasingly important.

People assimilate information in various ways, and adapting methods to individuals' cognitive styles and preferences is a necessity for effective learning. Recently, research has focused on four types of learning: classic/reading-writing, auditory, visual, and kinesthetic.

The classic learning system, based on writing and reading, has been a central pillar of education for a long period. Individuals who adopt this learning style use written materials, notes, books, and all forms of written content to assimilate information. A recent study has shown that students who employ reading/writing-based learning and assimilation strategies can enhance their analysis and synthesis abilities [25].

On the other hand, auditory-based learning involves processing information from the external environment through hearing. Individuals who use this mode retain information presented orally, such as lectures and verbal explanations. According to research conducted among students, those who participated in study groups and interactive discussions achieved better results in understanding and assimilating content [26].

A completely different way of assimilation is represented by visual learning, which involves using visual elements to retain and understand information.

Diagrams, charts, and other visual representations can facilitate the understanding of complex concepts. In this sense, students who have used illustrations and images to learn and assimilate have demonstrated a deep understanding of the subjects they have enhanced in this way [27].

Another mode of assimilation is constituted by kinesthetic learning, which is based on dynamics, movement, and physical involvement in the learning process. Students who learn through this mode prefer demonstrations, experiments, and practical activities. According to research, integrating certain hands-on activities into the education process can enhance students' motivation and understanding [28].

Furthermore, in recent times, emphasis has been placed on integrated approaches, which have become increasingly popular and valued. By combining elements from various learning styles, trainers and educators can develop complex and balanced learning environments. This approach involves adopting a multitude of educational strategies that can maximize efficiency in the learning process [29].

In a kind of conclusion, the classic/reading-writing, visual, auditory, and kinesthetic learning types represent a valuable beginning for understanding the cognitive diversity of individuals. In this sense, recent research has highlighted the need for adopting an integrated and flexible approach that considers individual preferences and provides a diverse range of learning modalities.

## 3. METHODOLOGY

To obtain the data, a test with 40 questions was administered to a group of 142 respondents, which was then input as data into the "Neuroshell" application. The "Beginner's Neural Network" module was chosen for parameter use because it allows the construction, adaptation, and execution of a complete and powerful neural network. This module was preferred due to its error backpropagation system, established on three levels of control, and a simplified universal architecture with optimal generalization capabilities for a variety of problems.

As the "Neuroshell" application operates in a modular fashion, meaning that after an icon is activated and executed, the program allows access to the next stage, the completion of all steps was pursued so that the algorithm is realized according to optimal parameters. During the processing stage, input variables were defined, and corresponding output variables were assigned. In the program, columns in the data table were labeled as either A or I, where I denoted any input variable and A denoted output variables [30].

Additionally, minimum and maximum values were established for each selected variable to be part of this process. These were set in a range from -1 to 1 or from 0 to 1, so that the network could recognize and interpret values within these intervals. After selecting the "Compute mins/maxes" option, minimum and maximum values, as well as average values and standard deviations for each variable, were automatically calculated. The minimum and maximum values closely approximate the real values, allowing the program to establish an acceptability and prediction margin for future inputs and applications. This is because if these values differ significantly from the real values, the network might lose its ability to recognize small differences between the data of interest [31].

In the case of the proposed model, it is important to use a structured method with multiple levels of intensity that are encompassed between a minimum and a maximum, to update the neural network to optimal parameters, which will define a fully updated structural model [32].

In this manner, the network can have a margin within which to establish relationships between the involved data and formulate hypotheses, thereby enabling the understanding of complex phenomena. Within the established boundaries, machine learning algorithms analyze data and propose new models without becoming confined to specific theories or pre-existing knowledge, resulting in increased efficiency for creating new data-driven models and even surpassing cognitive limits that were once associated with experience-based production.

If operational limits have been set appropriately, machine learning algorithms possess the ability to learn and adapt to new data without requiring explicit reprogramming by the user. This fact allows machine learning algorithms to evolve and adjust to an ever-changing environment, refining their previous knowledge and forming a new cognitive ecosystem. Therefore, automated learning algorithms can genuinely assist in making decisions, identifying necessary patterns, and formulating predictions through the analysis of the involved data [33].

The achieved data underwent an anonymization process by transforming name and surname variables into numerical indices, after which they were input into the application, and the computation of these actions is depicted in Figure 1.

Within the established working module, the network parameters were preset using its own algorithm for optimal operation and high performance, considering the learning rate, network inertia, as well as the number of hidden neurons, in such a way that it runs according to the implementation and training requirements demanded by such a project and based on the involved indices, as can be observed in Figure 2.

The next step consisted of training the network, an action undertaken in the "Learning" module, where inputs and outputs were automatically inserted to complete the system created. In this stage, the parameters corresponding to this module were set as follows:

a) The complexity of the problem was revealed by selecting the appropriate level for the problem executed within the program. Due to a reduced number of variables, the "Very Simple" option was chosen, directly proportional to the complexity level within the network. For this option, other factors were automatically determined by the program, such as the "Learning Rate," signifying the rate of learning, as well as "Momentum," defined by inertia, with preset values of 0.6 and 0.9, respectively.

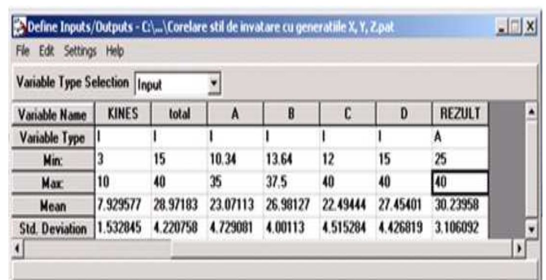
b) The number of hidden neurons is a value adjustable both automatically and manually. In the case of this application, a total of 17 neurons were allocated through automatic setting.

c) It is considered important for the network to possess predictive capacity regardless of any class differences among the introduced or forthcoming elements. To achieve this, a random compilation was chosen.

d) The calibration interval for the training session was set to 0, which is a neutral starting value.

All these settings and options can be observed in Figure 2 where the chosen method for training this network is displayed. After establishing and selecting this mode of operation, the network was then trained, as presented in Figure 3. During network training, the goal was to run enough epochs to allow the network to form and for the error to be minimized, ensuring that the formed network achieves enhanced efficiency, and its predictions are based on a larger number of executed epochs. In this context, after following these steps, it can be determined whether the network exhibits maximum performance or not, based on all its specific elements.

The network was stopped manually by a user-defined command after 102,922 epochs, with the minimum error of 0.0000279 sustained for 3,905 epochs, as beyond this point, the neural network ceased to make progress.


Define Inputs/Outputs - C:\...\Corelare stil de invatare cu generatiile X, Y, Z.pat

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Variable Type Selection: Input

| Variable Name | KINES | total | A | B | C | D | REZULT |
|---|---|---|---|---|---|---|---|
| Variable Type | I | I | I | I | I | I | A |
| Min: | 3 | 15 | 10.34 | 13.64 | 12 | 15 | 25 |
| Max: | 10 | 40 | 35 | 37.5 | 40 | 40 | 40 |
| Mean | 7.929577 | 28.97183 | 23.07113 | 26.98127 | 22.49444 | 27.45401 | 30.23958 |
| Std. Deviation | 1.532845 | 4.220758 | 4.729081 | 4.00113 | 4.515284 | 4.426819 | 3.106092 |

**Fig. 1.** Definition of Inputs and Outputs.

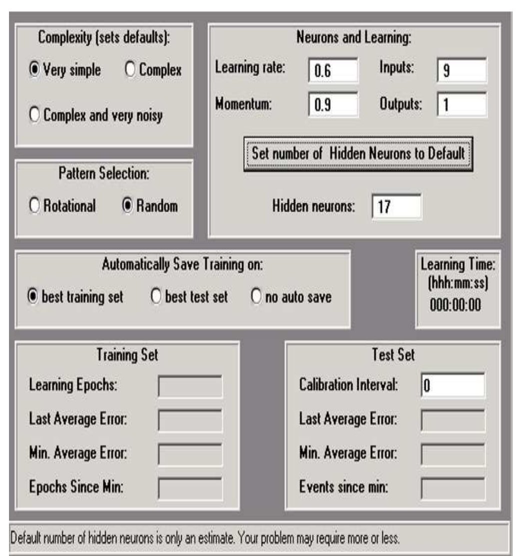


**Fig. 2.** Neural Network Parameter Setup.

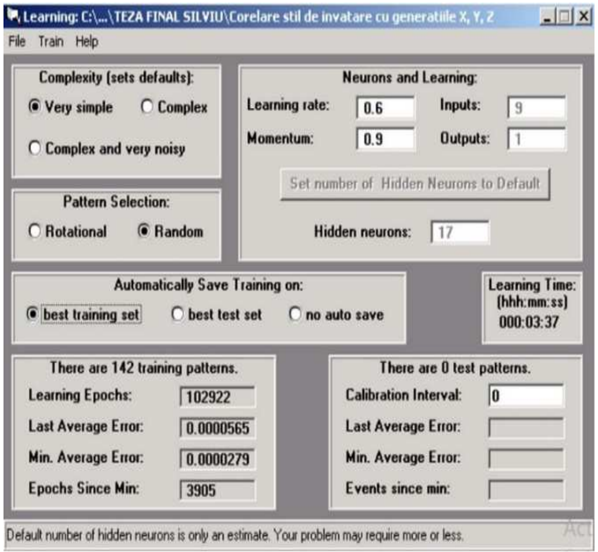


**Fig. 3.** Neural Network Training Module

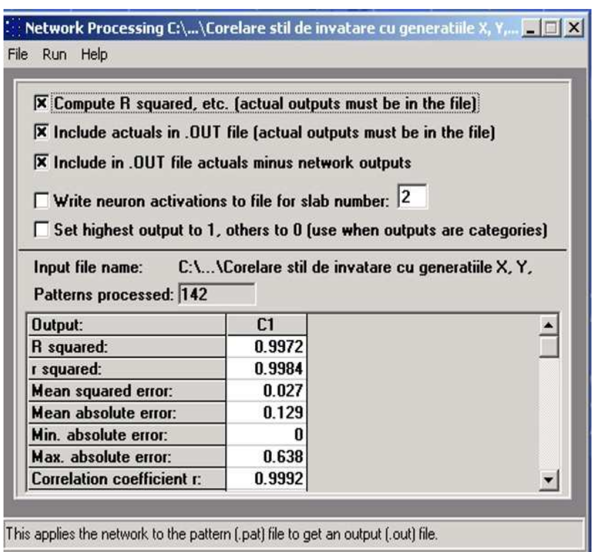


**Fig. 4** The Processing Module of the Network.

Following the automated processing of the data in the "Apply Neural Network" module, it can be observed that, upon executing the operations associated with this module through the "Start Processing" function, the network is well-structured and efficient.

In Figure 4, the Processing Module of the network is presented. After processing the test within this module, the "R Squared" indicator is noted as 0.9972, expressing the network's efficiency. "R Squared" is a statistical indicator used in cases of multiple regression analysis.

It compares the accuracy and efficiency of the created model with a standard model, where a perfect result is 1, and a good result is situated around that value.

The data's evolution can be observed within the program by attaching the original input file alongside the file containing the network's response. These can be comparatively analyzed within this program module.

This comparative mode is frequently used in similar applications as it allows the analysis of the evolution of a tracked process, which represents an important element in any such research.

This approach was chosen for this type of analysis. Moreover, this method facilitates easier extrapolation of the research-tracked data, making them more readily applicable for various other tests or exercises aimed at validating the new network.

Simultaneously, visual analysis becomes much more manageable for such a dataset, particularly when minor differences need to be identified, which can still lead to a significant impact on the efficiency of the network thus created.

In Figure 5, Comparative Analysis of Data Evolution, it can be observed that the difference between the first column, which contains values assigned to the variables on which the network has been set to make predictions, and the second column containing values for the variables predicted by the network, is represented in the third column.

The smaller the differences between these two columns, the better the network is training, which is also evident in our proposed model. Based on the obtained data, a set of 14 potential preferred learning and teaching styles has been established.

These styles are derived from the four basic styles: classic, auditory, visual, and kinesthetic. This set of 14 possibilities is illustrated in Fig. 6 Preferred Learning Styles.

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File Edit Format Help

Number of row with variable names (blank if none): 1

First row containing actual training data: 2

left/right arrow keys end edit

Size: 143 row 20 columns

Note: This is not a commercial spreadsheet and may not load fast enough for large files. The NeuroShell 2 Options men "datagrid" for details.

| | A | B | C | D |
|---|---|---|---|---|
| 1 | Actual(1) | Network(1) | Act-Net(1) | |
| 2 | 25.930000305176 | 25.962341308594 | -0.032341003418 | |
| 3 | 32.139999389648 | 32.040058135986 | 0.099941253662 | |
| 4 | 30.770000457764 | 30.655990600586 | 0.114009857178 | |
| 5 | 33.330001831055 | 33.229892730713 | 0.100109100342 | |
| 6 | 29.030000686646 | 28.915821075439 | 0.114179611206 | |
| 7 | 29.629999160767 | 29.355741500854 | 0.274257659912 | |
| 8 | 40.000000000000 | 39.899520874023 | 0.100479125977 | |
| 9 | 40.000000000000 | 39.947616577148 | 0.052383422852 | |
| 10 | 30.000000000000 | 29.822639465332 | 0.177360534668 | |
| 11 | 32.259998321533 | 32.268497467041 | -0.008499145508 | |
| 12 | 29.409999847412 | 29.258163452148 | 0.151836395264 | |
| 13 | 33.330001831055 | 33.107288360596 | 0.222713470459 | |
| 14 | 25.000000000000 | 25.137115478516 | -0.137115478516 | |
| 15 | 27.270000457764 | 27.287729263306 | -0.017728805542 | |
| 16 | 28.129999160767 | 27.915493011475 | 0.214506149292 | |
| 17 | 28.569999694824 | 28.501876831055 | 0.068122863770 | |
| 18 | 31.030000686646 | 30.962217330933 | 0.067783355713 | |
| 19 | 31.030000686646 | 30.817531585693 | 0.212469100952 | |

**Fig. 5** Comparative Analysis of Data Evolution.

| CL% | AUD% | VIZ% | KINES% | | | |
|---|---|---|---|---|---|---|
| Cla | Aud | Vis | Kin | Max | Sel | Pattern |
| 22.22% | 25.93% | 25.93% | 25.93% | 25.93% | Aud+Vis+Kin | Aud+Viz+Kin |
| 10.71% | 32.14% | 28.57% | 28.57% | 32.14% | Aud | Aud+Kin |
| 15.38% | 30.77% | 23.08% | 30.77% | 30.77% | Aud+Kin | Aud+Viz |
| 11.11% | 33.33% | 22.22% | 33.33% | 33.33% | Aud+Kin | Cla+Viz+Kin |
| 25.81% | 29.03% | 16.13% | 29.03% | 29.03% | Aud+Kin | Cla+Aud |
| 25.93% | 29.63% | 18.52% | 25.93% | 29.63% | Aud | Cla+Aud+Kin |
| 20.00% | 24.00% | 16.00% | 40.00% | 40.00% | Kin | Cla+Aud+Viz+Kin |
| 13.33% | 20.00% | 40.00% | 26.67% | 40.00% | Viz | Cla+Kin |
| 26.67% | 26.67% | 16.67% | 30.00% | 30.00% | Kin | Cla+Viz |
| 22.58% | 32.26% | 19.35% | 25.81% | 32.26% | Aud | Viz+Kin |
| 23.53% | 23.53% | 29.41% | 23.53% | 29.41% | Vis | Cla |
| 25.93% | 18.52% | 22.22% | 33.33% | 33.33% | Kin | Aud |
| 25.00% | 25.00% | 25.00% | 25.00% | 25.00% | Cla+Aud+Vis+Kin | Vis |
| 21.21% | 27.27% | 24.24% | 27.27% | 27.27% | Aud+Kin | Kin |

**Fig. 6.** Preferred Learning Styles.

In Figure 6 Preferred Learning Styles, the last column displays the model of possible and accepted learning styles synthesized from all four types of learning and the analysis of the preferred and accepted ones among them. In this regard, 14 patterns can be distinguished, namely:

1. The auditory style along with the visual and kinesthetic styles;
2. The auditory style along with the kinesthetic style;
3. The auditory style along with the visual style;
4. The classic style along with the visual and kinesthetic styles;
5. The classic style along with the auditory style;
6. The classic style along with the auditory and kinesthetic styles;
7. The classic style along with the auditory, visual, and kinesthetic styles;
8. The classic style along with the kinesthetic style;
9. The classic style along with the visual style;
10. The visual style along with the kinesthetic style.
11. The classic style;
12. The auditory style;

13. The visual style;
14. The kinesthetic style.

These styles represent an option as well as a preference for learning types. However, for each of these, we aim to develop a series of materials and course models that align with the current requirements in the field of education in future work.

## 4. CONCLUSION

The model we propose comes to the aid of the delicate situation triggered in education due to the pandemic context and the attempt to transition into the online environment, even though at present, traditional in-person classes are still being supported, alongside online and hybrid ones.

Furthermore, our aim was to develop a model that captures the reality of the current educational system, where three generations, namely X, Y, and Z, coexist, each having specific learning and assimilation preferences. It is crucial to establish a connection on both an ideological and practical level among these generations, leveraging the technological and informational explosion of our times.

In conclusion, we assert the necessity of an interactive predictive system that fosters education and continuous development. In this regard, we have proposed the creation of an intuitive and practical system for selecting and assigning the best-accepted and preferred learning model. To achieve this, we have involved neural networks in this endeavor, as they can provide a balanced and meticulous response.

Our proposal represents a challenge due to the technological impact on the socio-human aspect, leading to an interdisciplinary approach. Peeling back the layers of this concept, we find a rich seam of potential that stretches far beyond the classroom walls. Imagine an educational system that's not just about pouring information into passive vessels but about nurturing individual talents and predicting where each student might shine brightest. It's about creating a learning journey that's as unique as the individual embarking on it. Teachers would have a roadmap, informed by data, to guide each student, helping them overcome obstacles and reach their destination with confidence.

Our proposal is about recognizing the fact that all the strength of a company lies not only in the operating machines machines but also in the people who clearly run them.

By applying this predictive model, we can tailor exactly training programs to fit with the workforce, and not the other way around and this isn't just about improving the efficiency; it is about empowering the employees and giving them the knowledge and the tools they need to innovate and grow.

In this way, our concept develops bridges between industry and education, proving that the learning process is not only a destination but the journey itself that continues, from every classroom to the heart and brain of the economy.

## 5. REFERENCES


[1] Daniel, S. J., *Education and the COVID-19 pandemic*, Prospects: Comparative Journal of Curriculum, Learning and Assessment, Vol 49(1), pp 91-96, 2020.

[2] Viner, R. M., Russell, S. J., Croker, H., Packer, J., Ward, J., Stansfield, C. & Booy, R., *School closure and management practices during coronavirus outbreaks including COVID-19: a rapid systematic review*, The Lancet Child & Adolescent Health, Vol 4(5), pp 397-404, 2020.

[3] Armitage, R., & Nellums, L. B., *The COVID-19 response must be disability inclusive*, The Lancet Public Health, Vol 5(5), pp 257, 2020.

[4] Lee, J., *Mental health effects of school closures during COVID-19*, The Lancet Child & Adolescent Health, Vol 4(6), pp 421, 2020.

[5] Hodges, C. B., Moore, S., Lockee, B. B., Trust, T., & Bond, M. A., *The difference between emergency remote teaching and online learning*, https: // er.educause.edu/articles/2020/3/the-difference-between-emetgency-remote-teaching-and-online-learning

[6] Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., & Rubin, G. J., *The psychological impact of quarantine and how to reduce it: rapid review of the evidence*, The Lancet, Vol 395(10227), pp 912-920, 2020.

[7] Mayer, R. E., *Evidence-based principles for how to design effective instructional videos*, Journal of Applied Research in Memory and Cognition, Vol 10(2), pp 229-240, 2021.

[8] Holmes, W., Persson, J., Chounta, I. A., Wasson, B., & Dimitrova, V., *Artificial intelligence and education: A critical view through the lens of human rights, democracy and the rule of law*, Council of Europe, ISBN 978-92-871-9237-0, 2022.

[9] Durlak, J. A., Mahoney, J. L., & Boyle, A. E., *What we know, and what we need to find out about universal, school-based social and emotional learning programs for children and adolescents: A review of meta-analyses and directions for future research*. Psychological Bulletin, Vol 148(11-12), pp 765 - 782, 2022.

[10] Yeager, D. S., & Dweck, C. S., *What can be learned from growth mindset controversies?* American psychologist, Vol 75(9), pp 1269 - 1284, 2020.

[11] Hammoudi Halat, D., Soltani, A., Dalli, R., Alsarraj, L., & Malki, A., *Understanding and Fostering Mental Health and Well-Being among University Faculty: A Narrative Review*, Journal of Clinical Medicine, Vol 12(13), pp 4425 -4453, 2023.

[12] Anyichie, A. C., & Butler, D. L., *Examining culturally diverse learners' motivation and engagement processes as situated in the context of a complex task*, Frontiers in Education, Vol. 8, https://www.frontiersin.org/articles/103389/feduc.2023.1041946/full.

[13] Volante, L., DeLuca, C., Adie, L., Baker, E., Harju-Luukkainen, H., Heritage, M., Schneider, C., Stobart, G., Tan, K., Wyatt-Smith, C., *Synergy and tension between large-scale and classroom assessment: International trends,* Educational Measurement: Issues and Practice, Vol 39(4), pp 21-29, 2020.

[14] Chen, P., Powers, J. T., Katragadda, K. R., Cohen, G. L., & Dweck, C. S., *A strategic mindset: An orientation toward strategic behavior during goal pursuit*, Proceedings of the National Academy of Sciences, Vol 117(25), pp 14066-14072, 2020.

[15] DeMink-Carthew, J., & Olofson, M. W., *Hands-joined learning as a framework for personalizing project-based learning in a middle grades classroom: An exploratory study*, Resarch in Middle Level Education, Volume 43 (2), pp. 1 - 17, EISSN-1940-4476, 2020.

[16] Maier, M. H., *Group-Worthy Cooperative Learning Structures in the College Classroom*, Ed. Routledge, ISBN 9781003268192, 2023.

[17] Dada, D., Laseinde, O. T., & Tartibu, L., *Student-Centered Learning Tool for Cognitive Enhancement in the Learning Environment*, Procedia Computer Science, Vol 217(19), pp 507-512, 2023.

[18] Wichmann, F. A., & Geirhos, R., *Are Deep Neural Networks Adequate Behavioral Models of Human Visual Perception?*, Annual review of vision science, https://doi.org/10.1146/annurev-vision-120522-031739, 2023.

[19] Ciravegna, G., Barbiero, P., Giannini, F., Gori, M., Liò, P., Maggini, M., & Melacci, S., *Logic Explained Networks*, https://arxiv.org/abs/2108.05149, 2023.

[20] Pisarchik, A. N., & Hramov, A. E., *Coherence resonance in neural networks: Theory and experiments*, Physics Reports, Vol 1000, pp 1-57, ISSN 0370-1573, 2023.

[21] Parkhomenko, N., Otenko, I., Martynovych, N., & Otenko, V., *Application of Neural Networks in Prediction of Enterprise Development in Global Environment*, SCMS Journal of Indian Management, Vol 20(1), ISSN 0973-3167, 2023.

[22] Badiru, A. B., & Asaolu, O., *Handbook of Mathematical and Digital Engineering Foundations for Artificial Intelligence: A Systems Methodology*, CRC Press, ISBN 9781003247395, 2023.

[23] Caicedo, J. D., González, M. C., & Walker, J. L., *Public Transit Demand Prediction During Highly Dynamic Conditions: A Meta-Analysis of State-of-the-Art Models and Open-Source Benchmarking Infrastructure*, https://arxiv.org/abs/2306.06194, 2023.

[24] Nemitallah, M. A., Nabhan, M. A., Alowaifeer, M., Haeruman, A., Alzahrani, F., Habib, M. A., Elshafei, M., Abouheaf, M.I., Aliyu, M., Alfarraj, M., *Artificial intelligence for control and optimization of boilers' performance and emissions: A review*, Journal of Cleaner Production, Vol 417(8), ISSN 0959-6526, 2023

[25] Hattie, J., Visible learning: A Synthesis of over 800 Meta - analyses relating to achievement, Ed Routledge, ISBN 978415476188, 2008.

[26] Chen, L., Wang, Z., & Yang, Y., *Interactive Discussions Improve Learning Outcomes*, Journal of Educational Psychology, Vol 111(5), pp 870-886, 2019.
[27] Smith, J., Johnson, M., & Williams, R., *Visual Aids Enhance Conceptual Understanding*, Journal of Learning Science, Vol 25(3), pp 451-465, 2020.
[28] Martinez, A., Garcia, D., & Rodriguez, F., *Kinesthetic Learning and Student Motivation*, Journal of Educational Research, Vol 88(4), pp 454-466, 2019.
[29] Johnson, R., Miller, K., & Brown, S., *Integrating Learning Styles in Educational Practices*, Journal of Educational Psychology, Vol 118(1), pp 135-149, 2022.
[30] Camilotti, E., Furian, T. Q., Borges, K. A., Rocha, D. T. D., Nascimento, V. P. D., Moraes, H. L. D. S., & Salle, C. T. P., *Artificial neural networks for the management of poultry industry: a simulation based on the broiler production chain*, https://www.scielo.br/j/cab/a/yr4xpzkhvbszr9tnbpz9fhq/, 2023.
[31] Prostean, G., *Tehnici de inteligenţă artificială în management*, Ed. Orizonturi Universitare, ISBN: 978-973-638-299-4, p. 89, 2007.
[32] Cao, Z., Yin, T., Geng, G., Qian, X., Poh, L.H., Pang, S.D., *Model Updating with Neural Network Based on Component Model Synthesis*, https://doi.org/10.1007/978-981-19-7331-4_54, 2023.
[33] Yang, J., Marrone, M. and Amrollahi, A., "*What Makes AI Different? Exploring Affordances and Constraints - The Case of Auditing*", ECIS 2023, https://aisel.aisnet.org/ecis2023_rp.

## Metode si tehnici de eficientizare a sistemuluii educational prin folosirea retelelor neuronale

Prin contextul pandemic, s-a migrat masiv către noile tipuri de predare mixtă și online iar educația s-a văzut în fața unor provocări noi de mare anvergură. Odată cu sporirea noilor tehnologii de comunicare, a apărut problema menținerii dialogului educațional dintre membrii celor trei mari generații implicate în procesul educațional, și anume membrii generației X, ai generației Y și ai generației Z, la curent cu toate noile descoperiri. Identificarea metodelor de comunicare dintre aceste generații și abilitatea de a transmite și evalua cunoștințele acestora au devenit subiecte de cercetare. Cercetarea noastră se focusează asupra determinării unei corelații dintre tipurile de învățare acceptate, preferate și folosite și generațiile actuale aflate în procesul educațional iar provocarea constă în stabilirea unui model viabil. În acest sens, ne propunem să folosim inteligența artificială și capacitatea rețelelor neuronale pentru realizarea unui sistem predictiv capabil să determine și să propună metodele de învățare proprii fiecărui student.

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