

DESIGN AND EVALUATION OF AN INTELLIGENT AI- INFUSED E-LEARNING SYSTEM

Nagula Bhanupriya

Research Scholar

Dr. Rajeev Yadav

(Professor)

Glocal School of Technology & Computer Science

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ABSTRACT

Artificial intelligence is driving advancements in every industry as we enter the digital era. The potential that such devices, through human ingenuity and technology, can exhibit to guide society towards a successful and better modernity is immense in the fields of money, entertainment, welfare, health, and notably education. In this context, the next position paper will evaluate the advantages of artificial intelligence in terms of administrative organisation, in-presence learning, and distant learning through a non-formal exploratory literature review. First, let's define artificial intelligence as follows. Our goal is to examine the features and applications of these tech tools in educational contexts. We'll look at how artificial intelligence can be used in traditional education to assist and improve educational interventions. Students acquaint themselves with the best learning styles. Identifying the critical steps to make traditional education or online learning flexible are learning styles. Learning models have been proposed in the literature as a means of identifying learning styles; however, no software application that offers this freedom to choose and apply the best learning model is now widely accessible. This article proposes a framework for a tool that addresses this urgent requirement by taking into account various learning models and

artificial intelligence methods for identifying students' learning preferences. The tool will enable users to compare different learning models and identify which is best suited for a given situation.

Keywords: *Artificial Intelligence, E- Learning, Learning Styles, Distance education*

INTRODUCTION

Utilising artificial intelligence (AI) algorithms, customized education compares and contrasts classroom instruction with the needs of each learner. A student's interests, learning preferences, and strengths and limitations can all be taken into account when creating lesson plans, study guides, and activities. Students can work at their own speed and receive training that is specifically suited to meet their requirements when they use personalized learning. The applications of AI in e-learning that we will be going into in-depth are as follows:

- Schemes for recommending
- Smart Tutoring Strategies
- Individualized instruction
- Flexible Education Resources.

1.1. Learning Objective

1. Recognize the advantages and possibilities of AI in e-learning, such as instantaneous feedback and tailored teaching.
2. Discover how to use AI for automated assessment and grading, as well as how it may give teachers access to comprehensive analytics.
3. Examine how recommendation systems are used in e-learning and how they can change and get better over time in response to the preferences and actions of the students.
4. Analyse the application of AI-powered intelligent tutoring systems and their capacity to deliver individualized teaching and immediate feedback.

1.1 Schemes for recommending

Scheme for recommending employ artificial intelligence (AI) algorithms to evaluate a student's behaviour and preferences, and then suggest courses or other content that would be most

interesting or relevant to them depending on their needs. By allowing students to find content that is personalized for them, these technologies facilitate their ability to locate information quickly and effectively.

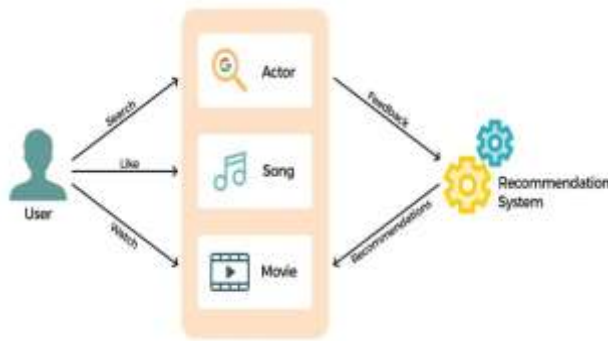


Figure1: Schemes of recommendation

We invite you to select a couple of your favourite Netflix titles when you create or add a new profile to your account. We "jump start" your recommendations using these titles. It's not necessary to pick a few titles you like. If you decide not to complete this step, we will provide you with a selection of popular and varied titles to get you started.

Your initial choices will be "superseded" once you begin watching titles on the site, and as you keep watching, the titles you have watched most recently will influence our recommendation system more than the titles you have watched previously

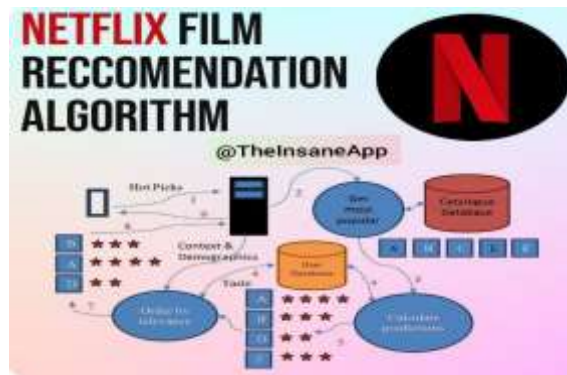


Figure2: Recommendation in contest of Netflix

AI recommendation systems are also capable of learning and changing over time. By taking into account fresh data and user behaviour, the system may continuously enhance its recommendations as more information is gathered and examined. Over time, the recommendations will grow more accurate, providing an even better user experience.

1.2 Smart Tutoring Strategies

By interacting with students directly through dialogue or other media like virtual reality, smart tutoring strategies mimic human tutors using artificial intelligence techniques like natural language processing and machine learning algorithms. Real-time feedback from STS may keep students interested and involved as they work at their own pace to understand difficult subjects.

The capacity to deliver individualized teaching is one of the key advantages of STS with AI. These tools can evaluate how well students do, pinpoint their advantages and disadvantages, and modify the curriculum as necessary. Since the student is only exposed to the content they need to learn, this may result in a more effective learning environment. In order to aid students in understanding the subject matter, STS can also offer advice and comments.

Microsoft, a well-known technology corporation, is one organisation that has implemented intelligent tutoring systems. With AI, STS can also develop and change over time. The system may continuously enhance its instruction by taking fresh data and student performance into account as additional data is gathered and examined. Microsoft understood that the training would get more and more effective over time, resulting in an even better educational experience.

1.3 Personalized Education

Using AI algorithms to assess students' learning preferences and customize lessons to meet their specific needs, personalized education is a method of teaching. This can involve creating lesson plans, study guides, and activities specifically suited to the learner's interests, learning preferences, and areas of strength and weakness. With customized learning, students receive education that is catered to their own needs while working at their own pace.

Students may concentrate on the areas where they need the most support and are more likely to stay interested and motivated as a result, which can make for a more successful and efficient learning experience. Furthermore, AI algorithms are able to track students' progress and modify individualized education as needed.



Figure 3: Personalized Education

One efficient method of promoting personalized education is to assign staff members to mentors or coaches who offer tailored advice, criticism, and encouragement. Employees that have mentors can set goals, overcome obstacles, and gain knowledge and insight from their experiences.



Figure4: Example of Personalized education

1.4 Flexible Education Resources

A state-of-the-art type of educational technology called adaptive learning platforms uses artificial intelligence (AI) to provide students with personalized and productive learning experiences. By offering the most pertinent content to each learner, the platform is able to maximize their learning experience. Students are able to concentrate on the precise areas in which they require

improvement as a result, which makes the learning process more effective and efficient. A new era of personalized, AI-powered learning is emerging, replacing the outdated one-size-fits-all approach to education with the aid of adaptive learning platforms.

2 LITERATURE REVIEW

Alam, A. (2021) Opportunities and Fears in AI in Education This work probably examines the possible uses of AI in education and might talk about worries or difficulties in putting it into practice.

Ayanwale et al. (2022): AI Education in Schools: Teachers' Readiness and Intention It appears that the readiness and desire of educators to use artificial intelligence in their lesson plans is the main emphasis of this study. It might address things that affect their intentions and level of preparation.

Bühler and colleagues (2022) Educating the Workforce of Tomorrow for the Fourth Industrial Revolution this essay is probably going to focus on methods and tactics for educating the next generation of workers so they can meet the demands of the fourth industrial revolution.

Chai and associates (2022): Simulating Learners' Behavioural Goals to Acquire AI To model and comprehend Chinese secondary school students' motivations and intentions to learn artificial intelligence, this research may make use of the Theory of Planned Behaviour and Self-Determination Theory.

Dhanvardini and colleagues (2022) - QG-SKI - Question Categorization and MCQ Production This work probably presents a sequential knowledge induction system or approach (QG-SKI) for question classification and multiple-choice question production.

3 EXISTING LEARNING THEORY MODEL

3.1 Felder & Silverman Learning Theory Model

There are four dimensions and two learning styles in each of the Felder and Silverman learning style models. Eight distinct learning styles can result in sixteen possible combinations. These four

aspects are visual/verbal, sensing/intuitive, sequential/global, and active/reflective. Working actively, applying the knowledge, and taking risks are the greatest ways for active learners to learn. Reflective learners, on the other hand, favour considering and reflecting on the material being studied. Students who learn best by feeling rely on their sensory experiences to absorb information and tangible materials. Conversely, abstract information with broad concepts, such theories and their underlying meanings, is what intuitive learners prefer to learn. Visual learners, such as those who study pictures, diagrams, and flow charts, retain information better than verbal learners, who learn best from spoken or written textual representations. The learning process of sequential learners is characterized by modest, incremental learning. On the other hand, global learners start by comprehending the bigger picture and employ a global and comprehensive cognitive process.

3.2 Kolb's learning theory model

Four different learning styles, each based on a four-stage learning cycle, are identified by Kolb's learning theory. The four phases of the learning cycle are: Active Experimentation (AE), Abstract Conceptualization (AC), Reflective Observation (RO), and Concrete Experience (CE). Two cycle states are combined to create each of the four learning styles. Diverging (CE/RO) learners tend to gather knowledge and solve issues using their imaginations since they would rather observe than participate. Assimilating (RO/AC) students like clear, rational instruction. To them, people are not as essential as ideas and concepts. Converging (AC/AE) learners utilise their knowledge to solve problems and apply it to real-world issues. They are less interested in people-oriented activities and instead favour technical duties. Learners who receive accommodations (AE/CE) are actively involved in tasks and depend more on instinct than reasoning. They often borrow analysis from others. Their preferred method of learning is experiential and hands-on.

3.3 Honey and Mumford learning theory model

Honey and Mumford learning styles were created by Peter Honey and Alan Mumford [6]. Their work is roused from Kolb's learning model. The four learning styles are activists, scholars, logical thinkers and reflectors. Activists are people who advance by doing. The learning exercises can be conceptualizing, critical thinking, bunch conversation, riddles, contests or pretend. Scholars students require models, thoughts and hypotheses to take part in the educational experience. Their

learning exercises incorporate models, insights, stories and they apply ideas hypothetically. Logical thinkers can try their learning actually. They learn better by applying learning in the event that reviews, in critical thinking and in conversations. Reflectors advance by watching, thinking and pondering what occurred. They like self-examination and character surveys, perception of exercises, input from others and meetings.

3.4 VARK learning theory model

To learn data, VARK represents Visual, Aural, Read/Compose, and Sensation abilities. Understudies' and educators' encounters filled in as the reason for Fleming and Factory's proposed model [5]. When addressing information as opposed to utilizing words, people who have a visual learning style utilize maps, outlines, diagrams, diagrams, stream graphs, and images. The inclination for information that is spoken or heard is alluded to as an aural learning style. Addresses, bunch conversations, radio, telephones, talking, web visit, and idea based discussion are the best learning mechanisms for students with this learning style. Word-based showcases of data are liked by those with a read/compose learning style. Peruse and compose manuals, reports, articles, and tasks with an accentuation on text-based info and result. An individual's inclination for training and experience, whether genuine or virtual, is alluded to as their sensation learning style. Reproductions, films, motion pictures, contextual investigations, and recordings are totally included.

4 DATA ANALYSIS AND INTERPRETATION

Theoretical concerns for instructional models include important variables that affect how effective learning style assessments are. A deeper knowledge of learning styles is facilitated by a higher count of attributes for students. The quantity of traits for students is crucial. Likewise, a wider range of learning styles is more adaptive, therefore the model's consideration of them is crucial. A significant factor is the amount of data in the student sample; bigger datasets support stable, broadly applicable models that can represent a wide range of student behaviours. Neural networks offer a versatile way to express the links between input information and learning styles. The number of nodes in the model indicates its complexity. There is also a trade-off when deciding

between Multilayer Perceptrons and decision trees. Multilayer Perceptrons, being neural networks, are better at capturing complex relationships but may be less interpretable than decision trees. Decision trees, on the other hand, offer interpretability, which helps in understanding decision-making processes. In order to match the unique objectives of learning style assessments with the model design, researchers must carefully traverse these factors.

AI/Model	Method Number of qualities for students	The quantity of different learning styles	The size of the student sample data	The number of nodes in the model
Felder Silverman/Multilayer Perceptron	4	5	25	13
Felder Silverman/Decision Tree	4	4	21	15
Kolb/Multilayer Perceptron	9	3	14	11
Kolb/Decision Tree	8	3	16	8

Table1: Comparison of generated Model

In contrast to the Kolb models, which have eight or nine attributes, the Felder Silverman models have four. This would suggest that the Felder Silverman models concentrate on a narrower range of student attributes. Different models take different numbers of learning styles into account. Felder Silverman/Decision Tree considers the least , while Kolb/Multilayer Perceptron considers the most .There are 14 to 25 students in the student sample. More robust and dependable models

can generally be produced with greater sample sizes. Model complexity can be inferred from the number of nodes in the model. With fifteen nodes, Felder Silverman/Decision Tree has the most, suggesting a more intricate decision tree structure.

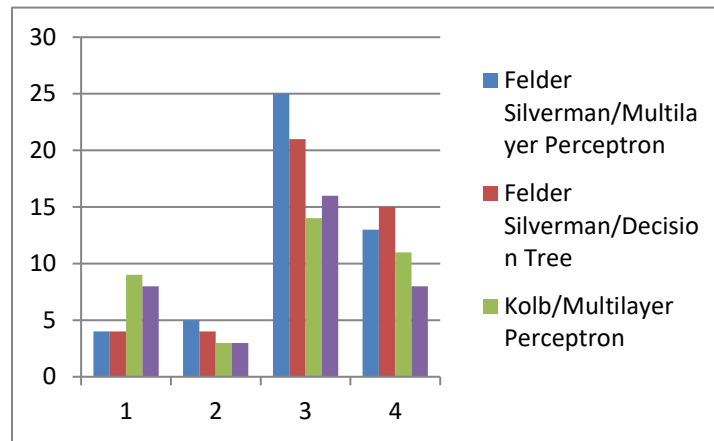


Figure1: Graphical representation of AI/Models

The assessment criteria for the instructional models offer a thorough comprehension of their classification efficacy. The metric that shows how accurately the models assign learning styles is the number of cases that are categorised. With 20 instances correctly identified, the Felder Silverman/Multilayer Perceptron, for example, showed great accuracy. On the other hand, the measure of the quantity of examples that are misclassified, like the five cases in the Felder Silverman/Decision Tree, highlights the possible shortcomings of the models. Model predictions and actual classifications can be compared with each other using the statistical measure of inter-rater agreement known as Kappa. Greater agreement is suggested by higher Kappa figures, such as the two that the Felder Silverman/Multilayer Perceptron was able to obtain. Furthermore, a smaller RMSE indicates better accuracy, as demonstrated in the Felder Silverman/Multilayer Perceptron's example with an RMSE of 0.0382. The Squared Root Mean Error (RMSE) is a measure of average difference between predicted and actual values. Together, these metrics provide information about the models' performance, which helps researchers and practitioners evaluate how well the models classify situations according to learning style requirements.

AI/Model	Appropriately categorized cases	Cases that were incorrectly classified	Kappa figures	Squared root mean error
Felder Silverman/Multilayer Perceptron	20	0	2	0.0382
Felder Silverman/Decision Tree	13	5	0.6052	0.2512
Kolb/Multilayer Perceptron	10	0	1	0.0251
Kolb/Decision Tree	8	1	0.657	0.1885

Table 2: Comparison of generated Model

Despite having perfectly classified every case, the Kappa figure (0.0382) is extremely low, suggesting poor agreement that goes beyond chance. 13 cases were correctly classified, 5 were not. Beyond chance, the moderate to significant agreement is indicated by the Kappa figure (0.6052). The average divergence of the predictions from the real data is shown by the squared root mean error (0.2512). a high Kappa figure (1) indicating complete agreement beyond chance and a perfect classification of all cases. At 0.0251, the squared root mean error is comparatively small. 8 cases

were classified properly, 1 erroneously. The Kappa value of 0.657 indicates a significant degree of agreement that goes beyond chance. The average divergence of the predictions from the real data is shown by the squared root mean error (0.1885).

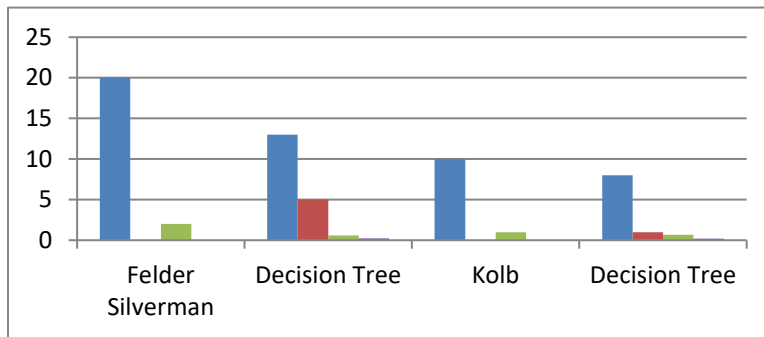


Figure 2: Graphical Representation of AI/Model

5 CONCLUSION

All in all, the investigation of computerized reasoning in training, as illustrated in this position paper, highlights its extraordinary possible across authoritative association, in-person learning, and distance schooling. The computerized period, driven by human resourcefulness and mechanical headways, presents a monstrous chance for simulated intelligence to add to a more fruitful and further developed innovation, especially in the domains of money, diversion, government assistance, wellbeing, and schooling. The characterized objective of this paper is to look at the highlights and uses of man-made brainpower in instructive settings, with a particular spotlight on its job in customary and web based learning conditions. The capability of computer based intelligence to help and upgrade instructive mediations is clear in its capacity to take special care of individual learning styles. Customary and internet learning can be made more adaptable by distinguishing and obliging assorted learning inclinations. While learning models have been proposed in the writing for of perceiving different learning styles, the shortfall of broadly open programming applications tending to this need is recognized. The proposed system in this article recommends the improvement of a device that use man-made reasoning to recognize understudies' learning inclinations through different learning models. This device means to give clients the

capacity to look at changed learning models and decide the most reasonable one for a given circumstance.

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