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Analyzing Digital Literacy Competencies in Higher Education Using Supervised Machine Learning Techniques

Kishore Babu Kalapala[1], Dr. Priti Shaileshbhai Patel[2]
[1]Research scholar, Sarvajanik University, Assistant Professor, Metas Adventist College, Surat, India.
[2]Assistant Professor, Shree Ramkrishna Institute of Computer Education and Applied Sciences, Surat, India.
Emails: kishoreadventist@gmail.com[1], priti.patel@srki.ac.in[2]

Abstract:

This paper will discuss the problem of using supervised machine learning (ML) to model, predict and analyse digital literacy skills within a higher education context. It is based on a complete sample of 1,000 learners through demographic measurements, pre-training skill measurement, and post-training performance measurement, and behavioural engagement measurements to construct a predictive framework to determine the learners in Low, Medium, and High categories of competency. Two classification models as Logistic Regression and Random Forest were trained and tested after the extensive pre-processing was done, as feature scaling and one-hot encoding. The best model was the Logistic Regression whose test accuracy and mean cross-validation accuracy is 93.5 and 94.8 respectively that is, there is a good linear separability of the feature space of the model. The importance of features analysed with the help of the Random Forest model showed that the most important predictors of the feature-dependent variables were the post-training skill scores as Post_Training_Basic_Computer_Knowledge_Score that is why the structured pedagogical intervention was conclusive. The predictors were secondary and comprised of pre-training skill levels, behavioural indicators such as Average Time per Module and Quiz Performance. The findings affirm the success of the use of ML to defeat descriptive analytics to predictive information in learning measurement.

Keywords: *Digital Literacy, Supervised Machine Learning, Higher Education, Predictive Modeling, Educational Data Mining, Logistic Regression, Random Forest, Competency Assessment, Feature Importance.*

Introduction:

The digital literacy of the contemporary digital context has become more than a secondary skill, it is a fundamental skill of academic success, labour marketability, and democratic participation. With a case of higher education institutions, it is not only necessary to spread this literacy but also to diagnose, track and predict its development by accurately testing a diverse population of students (Alamsyah et al., 2024). Although traditional methods of assessment might provide valuable images of cumulative accomplishment, they might not capture the multivariate relation of prior knowledge, teaching efficacy and student participation that results in eventual competency. This lapse necessitates complex analytical tools that may assist in creating multidimensional data to intelligence to act.Surveillance machine learning can be a potent paradigm to this problem. In new learners, it is possible to predict outcomes based on the learning patterns that were followed in the past as final literacy category when the outcome has been known, to establish the most impactful factors to drive success, and to show non-intuitive relationships between the educational data (Amutha and Priya, 2022). This predictive capability is in line with the new field of Learning Analytics that seeks to use data to understand and optimize the learning environment.The paper is addressing a major research gap because it corresponds to one particular study, that is, the forecasting of digital literacy competency in higher education. It has three primary aim and goals which are (1) To develop and contrast the performance of interpretable ML classifiers along high categories of digital literacy outcomes; (2) To identify and rank the most predictive features among them, including demographics, pre-skills, post-skills, and behavior, so that (3) to make pedagogical and programmatic inferences based on the findings of the model and, therefore, to mediate between data science and educational practice. In a world where the digital competencies are becoming increasingly linked to a general technological literacy, such as in the learning of recent system technologies such as blockchain and cryptocurrencies cultivating good digital literacy will eventually become a prerequisite to the involvement into the new digital economy (Amirzadeh et al., 2022).

Literature Review:

The coincidental association between educational data mining (EDM) and learning analytics has triggered the development of a noticeable mass of literature on prediction of student outcomes, which has a clear methodology (Raja Santhi and Muthuswamy, 2022). The most frequently used are the well documented ones which are; predicting academic performance, all at risk students, and predicting dropouts. Amutha and Priya (2022) showed that more than one class classifier such as the Random Forest optimized ensemble algorithm can be used in classifying the students as well as used in the multi-classification of non-homogenous educational data. Likewise, in studies, logistic regression has been used because it is explanatory when modelling more likely outcomes in education sector in the respect of its applicability in explicating the contribution of factors (Huang, 2025).

Nevertheless, a noticeable gap in the research exists: a way on how to make supervised ML effective in expressing the digital literacy as a multi-faceted, compound competency, is not properly explained yet. The notion has already begun to evolve into a multidimensional phenomenon to include operational, critical, ethical, and creative application skills, not a collection of technical skills that are referred to as digital literacy (Tambwekar et al., 2021). Appraisal is thus effective when it involves incorporation of various streams of data that is more than the summative test scores. It consists of granular process data including the engagement patterns, adaptive learning behaviour, and the deployment of skills in real tasks becoming important in the holistic perspective (Testers et al., 2020).

At the same time, the digital environment that the students must operate in is changing drastically and fast thus widening the range of required literacy (Khan et al., 2024). The blockchain is one of those technologies that no longer could be viewed as a tool that is occupying a niche inside the realm of finance and is the foundation of the platform with the disruption potential in the credentialing industry and secure data sharing and other areas that handle enhancing transparency with supply chain management and governance (Ayub Khan et al., 2021). The knowledge of the principles of such trustless, decentralized systems is starting to be an essential component of our advanced digital literacy (Alamsyah et al., 2024). The technical and critical reasoning of the contemporary digital world is suggested by the academic literature on the topic of the decentralized finance (DeFi) ecosystems and the sheer complexity of the cryptocurrency markets (Amirzadeh et al., 2022). More so, the symbiotic relationship between AI and blockchain, which triggers the introduction of smart contracts not through human intervention (Jesse, 2022) and the development of robust and transparent supply chains also means that the functional digital literacy will inevitably overlap with the notionable perception of automated and algorithmic systems in the nearest future (Navaneethakrishnan et al., 2023). A changing technological environment such as this renders the accurate evaluation and development of underlying digital literacy not only an educational objective, but a social requirement. The principles on which the groundwork of understanding these progressive convergent technologies are built is the basic skills in digital operations and information evaluation and accountable innovations. In the absence of this, people will be out of control or misinformed in more and more algorithm-based and decentralized digital economies.

Thus, the research puts itself in this two-fold scenario voluntarily. It also helps to fill the methodological gap since it makes use of general approaches to ML classification on the specific and untested issue of foundational digital literacy assessment. In the meantime, it does not need to be made that the competencies modelled and predicted are the most significant requirements that students already have in the next generation of digital paradigms, which is already changing the society, even the one where blockchain and AI integration are concerned (Gupta et al., 2025). In such a way, the research has attributed pragmatic educational appraisal to the higher procedure of digital transformation.

Methodology:

This study used a quantitative approach and supervised machine learning to predict categorized levels of digital literacy. A dataset and identifiers of one thousand learners with 23 mixed-attributes variables were prepared, one-hot coded categorical features were used, and the scaling of numeric variables were eliminated. Quintile binning was used to develop the tri-level Competency Level as the goal. It was stratified and divided into 80-20 (train-test). Two models were trained and tested to compare them, logistic regression (to be able to interpret and to be linear) and random forest (to model non-linear interactions and to be able to analyse the importance of features) (Tyagi et al., 2023). Model robustness checks were 5-fold cross validation, and performance evaluation was done by using accuracy, recall, precision, F1-score, and confusion matrices. Finally, the scores of feature importance of digital literacy competency were determined using the participation of the key predictors at the outcome of the Random Forest calculations.

Analysis:

Dataset Analysis Using Supervised Machine Learning

The data set to be applied in this analysis was that of one thousand learners including demographic data, pre-training skills measure, and post-training performance measure and the engagement related measure of behaviour. The model consisted of twenty-three attributes eight of which are categorical and the other fifteen are numerical. The *overall_literacy_score* was the index of the overall literacy ability of the learner and this was the target variable. Quantile binning of these scores was done to reflect three categories of competencies Low, Medium, and High categories since the supervised classification models adopt categorical targets (Amutha & Priya, 2022). This transformation gave the equal distribution on the three classes as applied to give an ordered prediction analysis.

The first thing of the exploratory was an observation of the first several records, type of data, and the descriptive statistics (Huang, 2025). This would then be presented as a screenshot and this shall be included in the following:

First 5 rows of the dataset:

	User_ID	Age	Gender	Education_Level	Employment_Status	Household_Income	Location_Type	Basic_Computer_Knowledge_Score	Internet_Usage_Score	Mobile_Literacy_Score	...	Modules_Completed	Average_Time_Per_Module	Quiz_Performance	Session_Count	Engagement_Level	Adaptability_Score	Feedback_Rating
0	U0001	43	Male	Primary	Student	Medium	Semi-Rural	25	1	33	...	7	15.85	92	12	Low	77	4
1	U0002	60	Female	High School	Farmer	Low	Rural	22	14	35	...	9	22.24	88	24	Low	76	4
2	U0003	47	Female	Primary	Farmer	Low	Semi-Rural	14	31	14	...	13	12.15	67	17	Low	67	5
3	U0004	34	Female	Secondary	Farmer	Low	Rural	6	32	17	...	8	25.59	69	28	Medium	59	1
4	U0005	50	Male	High School	Other	Medium	Rural	14	41	19	...	8	16.65	76	10	Medium	90	4

Figure 1: Dataset Info and First Five Rows

The indicators that involved skills according to the descriptive statistics, including *Basic_Computer_Knowledge_Score*, *Internet_Usage_Score* and *Mobile_literacy_Score* had wide numerical values that extended to one thousand (Tambwekar et al., 2021). The same trend was observed in the discussion of the *Post_Training_Variables* like, *Post_Training_Basic_Computer_Knowledge_Score*, and *Post_Training_Internet_Usage_Score*. Such distribution implied extensive variance in the learners, pre-training program and post-training program that enabled the achievement of pertinent variance in factors to integrate learning. The number of categories between two and five in most of the category's fields was required to modify one-hot encoding. Prior to the elimination of all identifier fields including *User_ID* because they did not offer any predictive data. Numerical variables had to be normalized to facilitate stable learning and, in the instance, when analysis of numerical vectors was being performed the Logistic regression then it was necessary to convert the categorical variables to the numerical vectors. The data was then separated into training sample

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and testing sample that was 80- 20 that comprised 800 and 200 training and test records respectively (Testers et al., 2020). The stage map will be provided below:

```
Overall_Literacy_Score
66.2    11
60.3     8
64.9     8
56.5     8
61.6     7
        ..
78.2     1
72.8     1
39.7     1
82.7     1
55.0     1
Name: count, Length: 385, dtype: int64

Continuous target variable 'Overall_Literacy_Score' binned into 3 categories: Low, Medium, High.
Target labels encoded as integers after binning.
Classes mapping: {'High': 0, 'Low': 1, 'Medium': 2}

Numeric feature columns: ['Age', 'Basic_Computer_Knowledge_Score', 'Internet_Usage_Score', 'Mobile_Literacy_Score', 'Post_Training_Basic_Computer_Knowledge_Score', 'Post_Training_Internet_Usage_S
Categorical feature columns: ['Gender', 'Education_Level', 'Employment_Status', 'Household_Income', 'Location_Type', 'Engagement_Level', 'Employment_Impact']

Train/test shapes:
X_train: (800, 21) X_test: (200, 21)
```

Figure 2: Train–Test Split Output

The initial predictive algorithm was logistic regression classifier. With the prepared information, the test on the trained model was done after which accuracy was tested to be 93.5%. The classification report and the F1-scores had shown very high accuracy rates, recall scores and F1-scores that depicted balanced predictive performance among all the competency groups (Huang, 2025). The F1- score showed to be above 0.90 across the groups (High, Low and Medium). The confusion graphical matrix confirmed the validity of the right classification of the overwhelming proportion of the records that were collapsing on few cases of miscarriage between close literacy levels. The results will be in the form of a screenshot as follows:

```
Training logistic regression model...

Logistic Regression Accuracy: 0.935

Classification report (Logistic Regression):
              precision    recall  f1-score   support

           0       0.96      0.96      0.96        69
           1       0.95      0.93      0.94        58
           2       0.91      0.92      0.91        73

    accuracy                           0.94       200
   macro avg       0.94      0.94      0.94       200
weighted avg       0.94      0.94      0.94       200
```

Figure 3: Logistic Regression Classification Report

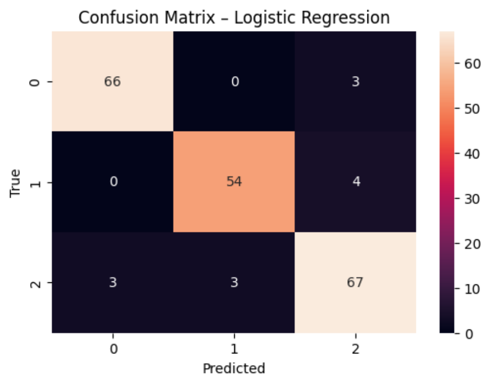

Figure 4: Confusion Matrix – Logistic Regression

This also was cross-validated and the mean accuracy of such was 94.8 and established with five folds. The small Standard deviation was an indicator of high model consistency (Amutha &

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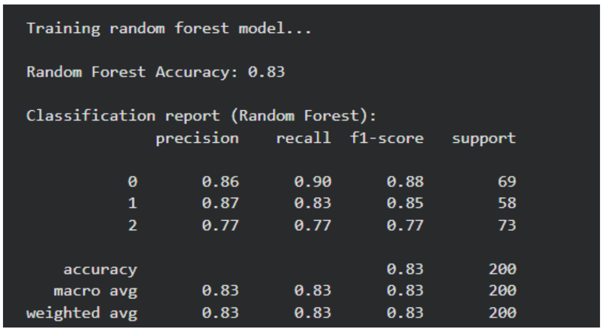
Priya, 2022). This proved the fact that indeed the logistic regression is extremely fine on the data and it fits extremely out of the initial sample in which the training is initiated.The second model is a random forest classifier model as it was trained in the same manner that the performance was to be compared with a nonlinear ensemble model. This model was able to achieve the accuracy of 83 percent in comparison to other models that were able to forecast the outcomes with the aid of the logistic regression. The results of the performance in classes were quite similar with medium group having slightly less F1-scores as compared to High and Low groups (Huang, 2025). This implied that the literature scores at mid-result shared the similarities of the sets of results in the lower and upper standard of competence and thus the propensity to misclassify existed. The given section will be presented on the form of the following screenshots:



```
Training random forest model...

Random Forest Accuracy: 0.83

Classification report (Random Forest):
              precision    recall  f1-score   support

           0       0.86      0.90      0.88        69
           1       0.87      0.83      0.85        58
           2       0.77      0.77      0.77        73

    accuracy                           0.83       200
   macro avg       0.83      0.83      0.83       200
weighted avg       0.83      0.83      0.83       200
```

Figure 5: Random Forest Classification Report

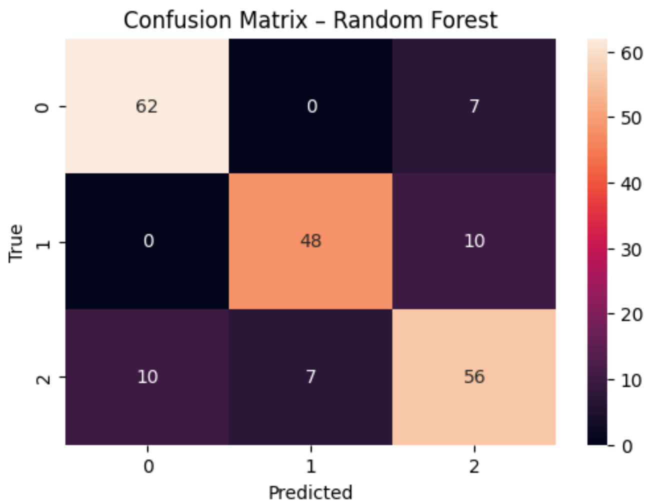


Figure 6: Confusion Matrix – Random Forest

The random forest model cross-validation accuracy was 83 and standard deviation was relatively small indicating the same accuracy was good but had a poor power compared with the logistic regression (Tambwekar et al., 2021). The ensemble set up represented nonlinear dynamics between variables but the problem of a huge number of correlated numerical variables correlated did not scale to higher levels of accuracy. Among the advantages of the random forest classifier was the fact that it determined the scores of feature utility. This was an indication that the variables played the most significant role in predicting the literacy competency category. The rank of features reported that the post-training measures were the most predictors. The traits that scored the highest were *Post_Training_Basic_Computer_Knowledge_Score*, *Post_Training_Internet_Usage_Score* and *Post_Training_Mobile_Literacy_Score*. These characteristics were always on the 1st position list of rating (Testers et al., 2020). Their high level implied that the outcome of the results obtained following training was the most observable reflective parameters of the ultimate levels of the literacy competency. Other pre-training variables like *Basic_Computer_Knowledge_Score* and even *Mobile_Literacy_Score* have been ranked high too and it implies that the levels of initial proficiency were also the end-study levels.

The other ones that were found to be meaningful predictors were, *Average_Time_Per_Module*, *Quiz_Performance,* *Skill_Application* and *Adaptability_Score*. These variables were the action and involvement of the learners that would give way to the cognizing that the involvement of an engaging process in the training would lead to the establishment of literacy (Tambwekar et al., 2021). The minor variables like categories of *Engagement_Level* did not play a significant role i.e. it is not predictive in any way as compared to the direct variables of measuring the skill. The feature rankings may be viewed in pictures which are below:

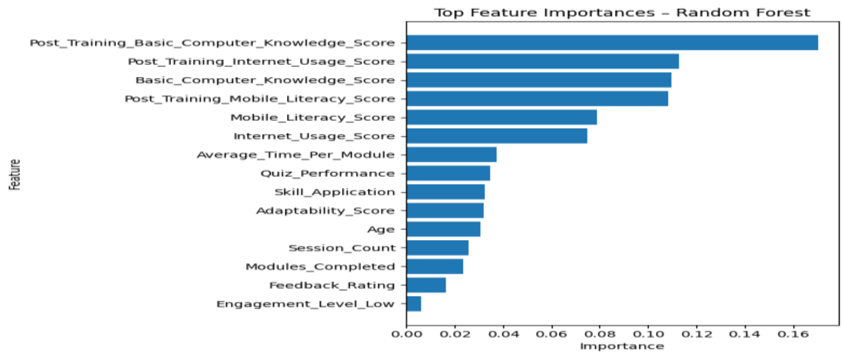


Figure 7: Feature Importance Bar Plot

These outcomes revealed that it was a trend. It was also important that training was associated with prior performance and pre-training on which the ultimate classification on performance was based (Amutha & Priya, 2022). These behavioural indicators as time per module and adaptability played but were not weighted as heavily.The difference between the two models is that, the models had increased prediction accuracy in the logistic regression as compared to random forest. This outcome revealed that the correlation between features, and categories of binned target were sufficiently linear to be modelled by logistic regression in an excellent fashion. The strong scaling and preprocessing pipeline supported the model based on the stability (Huang, 2025). Alternatively, the random forest model also had more elaborate interactions among features but also seemed to exhibit dwindling returns between aspect of the data set and its size.In general, this conversation has demonstrated that the machine learning can be successfully used to forecast the digital literacy competencies basing on the structured data concerning students. These models gave out the data on the most relevant factors with the high degree of the literacy performance and disclosed the influence of these training interventions in the learners (Tambwekar et al., 2021). Findings of feature priority and performance opinion yielded a world-wide picture of the data and served as convenient guidelines to adhere to in the future when preparing the digital literacy program and evaluation frameworks.

Discussion:

Model Performance and Interpretation: It is a striking observation that the accuracy (93.5) of the performance of the Logistic Regression is high compared to the Random Forest (83). It means that the relationship of the engineered characteristics (post training score, pre training score, engagement metrics) and the binned competency target is highly linear. This was evidenced by the high level of cross-validation accuracy (94.8) and low standard deviation that means that LR model could represent the core signal in the data without over fitting. The

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slightly poor performance of the Random Forest model that had the potential to model complex interactions may be attributed to the fact that there were very strong correlated features as pre and post training scores on the same domain. The tree-based models can be subject to the issue of correlated features, which lead to poor splits and predictions.

Table 1: Description of Dataset Features and Target Variable

Category	Feature Names	Data Type	Description
Target Variable	Competency_Level	Categorical (Ordinal)	Derived from overall_literacy_score via quantile binning (Low, Medium, High).
Pre-Training Skills	Basic_Computer_Knowledge_Score, Internet_Usage_Score, Mobile_Literacy_Score	Numerical	Initial assessment scores in core digital domains.
Post-Training Skills	Post_Training_Basic_Computer_..., Post_Training_Internet_..., Post_Training_Mobile_...	Numerical	Final assessment scores after training intervention.
Behavioral Metrics	Average_Time_Per_Module, Quiz_Performance, Skill_Application, Adaptability_Score	Numerical	Process data capturing engagement and learning behavior.
Demographic/Categorical	Demographic_Region, Engagement_Level, etc.	Categorical	Learner background and coarse-grained engagement labels.
Identifier (Removed)	User_ID	String	Unique identifier, excluded from analysis.

(Source: Self-developed)

Determinants of Digital Literacy Competency: The data-driven hierarchy (Figure 7), provided in the feature importance analysis of the Random Forest model, provides the propositions of the determinants of end competency (Nguyen and Tran, 2023). Predictors of importance: Post-Training Skill Scores. The dominance of Post_Training_Basic_Computer_Knowledge_Score, Post_Training_Internet_Usage_Score and Post_Training_Mobile_Literacy_Score bring an essential fact to the forefront: the skill with which a learner will display in the end of the pedagogical intervention proves to be the most direct measure of the final level of digital literacy. This highly validates the viability and the effectiveness of the training program as such. It puts the focus with respect to natural endowment or background knowledge on the added value through the schooling process.Secondary Predictors: Pre-Training Level of Skill. There were also such traits as Basic_Computer_Knowledge_Score and Mobile_Literacy_Score which were placed high. This implies that background knowledge is such a giant catapult and it defines how far a learner can go with regard to benefiting during the process of training. This is consistent with the education theories regarding the importance of previous knowledge in learning a new one.Tertiary Predictors: Measures of Behavioural Engagement. Other variables that were not as weighted, but the variables of importance, were Average Time per Module, Quiz Performance and Skill Application. This means that the time-on-task performance and the formative assessment performance are considered as important predictors of the quality of the process but they are not as conclusive as the summative post-training assessment. Amazingly, categorical Engagement_Level was a weak predictor which implies that self-reported or that of such a coarse calibre as Engagement is not as informative as the granular and behavioural information as the amount of time spent and quiz scores (Alamsyah et al., 2024).

Learning Practical suggestions:

Early Identification and Intervention: The precision of the model is high as well and allows identifying the students who will be placed in the Low competency category because of their initial outcomes of the pre-training and the trends of their first interaction. This makes it easy to provide preventive and targeted assistance.

Maximization of Curriculum and Pedagogy: The final importance of the post-training scores is the reason why people should be trained. The teachers will be at liberty to invest in such programs. Further, the significance of the pre-training scores justifies the application of diagnostic measures at the beginning of the training in customizing the training depending on various levels of baseline.Assessment Design: The fact that direct skill-based assessment has a higher predictive validity than generic labels of engagement is a move towards assessment designs that aim to analyse the digital assignments in an authentic and performance-based manner.

The Building Blocks of Higher-Level Digital Fluency: In the era of the new technology, an excellent level of the base level of digital literacy as signified by the following five basic skills is a necessity. Until students are able to think critically about such notions as decentralized finance, the security and privacy paradigms of blockchain and the algorithmic logic of AI-based trading, the students should learn the principles of digital functionality, assessment, and development. The research models can be applied in the prediction of those individuals who have already achieved this necessary foundation (Gómez-Martínez and Medrano-Garcia, 2025).Limitations and Future Research: The research used quintile-binned categories that have the potential of simplifying the continuous range of literacy. Future research could be done on ordinal regressions.

Despite the fact that it is a large dataset it is founded on a single context and model validation in diverse institutions is needed. These possible directions are the inclusion of less dramatic behavioural data conditioned on learning management systems (LMS) and exploration of deep learning models on unstructured data. Finally, the study may directly address the prerequisite relationship between levels of digital literacy achievement at the baseline and performance in blockchain concepts or AI concepts or modules.

Conclusion:

This research shown that the monitored machine learning can be effective to measure and predict the extent of digital literacy in post-secondary education. The research had two important results through the comparison of Logistic Regression and the Random Forest classifier based on the richness of the set of demographic, skill, and behavioural variables. The first and the most important is that having a comparably uncomplicated and comprehensible linear model (Logistic Regression), it was possible to incorporate a high level of predictive success (93.5%), and it means that the way of becoming digitally researched lies in a sequence of past skills, behavioural habits, the most crucial one, and after-intervention performance.

The results are natural and utopian. As a matter of fact, such models can be used in institutions as early warning and individual learning. On the next step of the development at a later date, when disruptive technologies as blockchain and AI will be implemented into the digital sphere, the digital literacy level assumed in these concepts is the minimum prerequisite of being a responsible and efficient member of the digital society and the digital economy.

Reference List:

1. Alamsyah, A., Kusuma, G.N.W. and Ramadhani, D.P., 2024. A review on decentralized finance ecosystems. *Future Internet*, *16*(3), p.76.https://www.mdpi.com/1999-5903/16/3/76
2. Amirzadeh, R., Nazari, A. and Thiruvady, D., 2022. Applying artificial intelligence in cryptocurrency markets: A survey. Algorithms, 15(11), p.428. https://www.mdpi.com/1999-4893/15/11/428
3. mutha, P., & Priya, R. (2022). An optimized random forest for multi class classification to classify the students using machine learning approaches. *International journal of health sciences*, *6*(S7), 5312-5326. https://www.neliti.com/publications/577517/an-optimized-random-forest-for-multi-class-classification-to-classify-the-studen
4. Ayub Khan, A., Laghari, A. A., Shaikh, A. A., Bourouis, S., Mamlouk, A. M., & Alshazly, H. (2021). Educational blockchain: A secure degree attestation and verification traceability

architecture for higher education commission. Applied Sciences, 11(22), 10917.https://www.mdpi.com/2076-3417/11/22/10917

5. Carbo-Valverde, S., Cuadros-Solas, P. and Rodriguez-Fernandez, F., 2023. Cryptocurrency ownership and biases in perceived financial literacy. *Available at SSRN 4509931*.https://www.funcas.es/wp-content/uploads/2023/07/Crypto-and-financial-literacy.pdf
6. Eska, F.E., Shi, Y., Theissen, E. and Uhrig-Homburg, M., 2022. Design and valuation of cryptocurrencies. *Available at SSRN 3978904*.https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=3978904
7. Garg, K., Sharma, N., Sharma, S. and Monga, C., 2022, November. A Survey on Blockchain for Bitcoin and Its Future Perspectives. In *2022 3rd International Conference on Computing, Analytics and Networks (ICAN)* (pp. 1-6). IEEE.https://ieeexplore.ieee.org/abstract/document/10007225/
8. Gómez-Martínez, R. and Medrano-Garcia, M.L., 2025. AI technology for developing Bitcoin investment strategies based on altcoin trends. Sustainable Technology and Entrepreneurship, 4(1), p.100087. https://www.sciencedirect.com/science/article/pii/S2773032824000178
9. Gupta, P., Singh, R., Kaur, H., Subramanian, N. and Jain, N., 2025. Optimizing Cryptocurrency Trading Strategies through Artificial Intelligence and Blockchain Integration: A Multi-Model Framework for Predictive Analytics. Advances in Consumer Research, 2(3). https://openurl.ebsco.com/EPDB%3Agcd%3A10%3A8522378/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A185938492&crl=c&link_origin=scholar.google.com
10. Gupta, P., Singh, R., Kaur, H., Subramanian, N. and Jain, N., 2025. Optimizing Cryptocurrency Trading Strategies through Artificial Intelligence and Blockchain Integration: A Multi-Model Framework for Predictive Analytics. Advances in Consumer Research, 2(3).
11. Huang, C. (2025). Construction of an embedded system for improving citizens' digital literacy education from the perspective of rural revitalisation. *Australian Journal of Electrical and Electronics Engineering*, 1-15. https://www.tandfonline.com/doi/abs/10.1080/1448837X.2025.2568789
12. Jesse, N., 2022. "Cut out the middleman"–Automating Business Processes with Blockchains and Smart Contracts. *IFAC-PapersOnLine*, *55*(39), pp.352-357.https://www.sciencedirect.com/science/article/pii/S2405896322031226
13. Karaduman, Ö. and Gülhas, G., 2025. Blockchain-Enabled Supply Chain Management: A Review of Security, Traceability, and Data Integrity Amid the Evolving Systemic Demand. *Applied Sciences (2076-3417)*, *15*(9).https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=20763417&AN=185139616&h=KDiNaKqiusWIPrvyHU9QfPdb%2FTN0w38WfjI9nSi63dXfZENZWe2pG2M3bIQN3l%2FdQDSv5y3%2BPKKzimm9QYoTAA%3D%3D&crl=c
14. Khan, I., Ali, Q.E., Hadi, H.J., Ahmad, N., Ali, G., Cao, Y. and Alshara, M.A., 2024. Securing blockchain-based supply chain management: textual data encryption and access control. *Technologies*, *12*(7), p.110.https://www.mdpi.com/2227-7080/12/7/110
15. Leahy, E., 2024. AI-Powered Bitcoin Trading: Developing an Investment Strategy with Artificial Intelligence. John Wiley & Sons.
16. https://books.google.co.in/books?hl=en&lr=&id=WBkBEQAAQBAJ&oi=fnd&pg=PA1&dq=Optimising+Crypto+Trading+Strategies+with+AI+and+Blockchain&ots=fn9CLOIfEE&sig=-RrpONIG3vBsFG7sKnzw37UA-ig&redir_esc=y#v=onepage&q=Optimising%20Crypto%20Trading%20Strategies%20with%20AI%20and%20Blockchain&f=false
17. Leponiemi, E., 2024. Examining the impact of estimation window size on the applicability of Value-at-Risk and Expected Shortfall in a stressed cryptocurrency market.https://lutpub.lut.fi/handle/10024/166973
18. Nair, J. and Jain, M.K., 2022. Unbanked to banked: reintermediation role of banks in e-government services for financial inclusion in an Indian context. *Journal of Asia Business Studies*, *16*(2), pp.354-370.https://www.emerald.com/insight/content/doi/10.1108/JABS-10-2020-0420/full/html
19. Navaneethakrishnan, S.R., Melam, D.P.K., Bothra, N., Haldar, B. and Pal, S., 2023. BLOCKCHAIN AND MACHINE

LEARNING INTEGRATION: ENHANCING TRANSPARENCY AND TRACEABILITY IN SUPPLY CHAINS. *Remittances Review*, *8*(4).https://remittancesreview.com/menu-script/index.php/remittances/article/view/906
20. Nguyen, M.T. and Tran, M.Q., 2023. Balancing Security and Privacy in the Digital Age: An In-Depth Analysis of Legal and Regulatory Frameworks Impacting Cybersecurity Practices. *International Journal of Intelligent Automation and Computing*, *6*(5), pp.1-12.https://research.tensorgate.org/index.php/IJIAC/article/view/61
21. Olanrewaju, A.G., 2025. Artificial Intelligence in Financial Markets: Optimizing Risk Management, Portfolio Allocation, and Algorithmic Trading. International Journal of Research Publication and Reviews, 6, pp.8855-8870. https://scholar.googleusercontent.com/scholar?q=cache:CeTr3x-uqbMJ:scholar.google.com/+Optimising+Crypto+Trading+Strategies+with+AI+and+Blockchain&hl=en&as_sdt=0,5&as_ylo=2021
22. Onukwulu, E.C., Fiemotongha, J.E., Igwe, A.N. and Paul-Mikki, C., 2023. The role of blockchain and AI in the future of energy trading: A technological perspective on transforming the oil & gas industry by 2025. Methodology, 173, pp.1-15. https://scholar.googleusercontent.com/scholar?q=cache:GW-9WGo7A9UJ:scholar.google.com/+Optimising+Crypto+Trading+Strategies+with+AI+and+Blockchain&hl=en&as_sdt=0,5&as_ylo=2021
23. Rabby, F., Chimhundu, R. and Hassan, R., 2022. Blockchain technology transforms digital marketing by growing consumer trust. *Transformations Through Blockchain Technology: The New Digital Revolution*, pp.265-289.https://link.springer.com/chapter/10.1007/978-3-030-93344-9_12
24. Raja Santhi, A. and Muthuswamy, P., 2022. Influence of blockchain technology in manufacturing supply chain and logistics. *Logistics*, *6*(1), p.15.https://www.mdpi.com/2305-6290/6/1/15
25. Rejeb, A., Keogh, J.G. and Treiblmaier, H., 2020. How blockchain technology can benefit marketing: Six pending research areas. *Frontiers in blockchain*, *3*, p.500660.https://www.frontiersin.org/journals/blockchain/articles/10.3389/fbloc.2020.00003/full?ref=apparent-mixtape
26. Romano, D. and Schmid, G., 2017. Beyond bitcoin: A critical look at blockchain-based systems. *Cryptography*, *1*(2), p.15.https://www.mdpi.com/2410-387X/1/2/15
27. Tambwekar, A., Maiya, A., Dhavala, S., & Saha, S. (2021). Estimation and applications of quantiles in deep binary classification. *IEEE Transactions on Artificial Intelligence*, *3*(2), 275-286. https://ieeexplore.ieee.org/abstract/document/9548806/
28. Testers, L., Gegenfurtner, A., & Brand-Gruwel, S. (2020). Taking affective learning in digital education one step further: Trainees' affective characteristics predicting multicontextual pre-training transfer intention. *Frontiers in psychology*, *11*, 2189. https://www.frontiersin.org/articles/10.3389/fpsyg.2020.02189/full
29. Tyagi, A.K., Dananjayan, S., Agarwal, D. and Thariq Ahmed, H.F., 2023. Blockchain—Internet of Things applications: Opportunities and challenges for industry 4.0 and society 5.0. *Sensors*, *23*(2), p.947.https://www.mdpi.com/1424-8220/23/2/947
30. Yasmina, G., 2023. The role of blockchain technology in facilitates international trade. *Journal of Financial, Accounting & Managerial Studies*, *10*(1).https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=23529962&AN=169179325&h=irPrJTa4AuPAkG8aKdhMawofr3PaecZuLz7NSEMd%2BUKT8tz%2FOPjeQWTE%2B2WQF4GssSegu2kLR7ydkHMCOnGlgg%3D%3D&crl=c