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Measuring Computational Psychometrics Analysis Motivational Level in Learner's using Different Parameters through Deep Learning Algorithm

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ABSTRACT

Learning is an ongoing process irrespective of age, gender and geographical location of acquiring new understanding, knowledge, behaviours, skills, values, attitudes, and preferences. Formative assessment methods have emerged and evolved to integrate learning, evaluation and education models. Not only is it critical to understand a learner's skills and how to improve and enhance them, but we also need to consider what the learner is doing; we need to consider navigational patterns. The extended learning and assessment system, a paradigm for doing research, captures this entire view of learning and evaluation systems. The function of computational psychometrics is to facilitating the translation from raw data to meaningful concepts. In this research study, several factors are considered for psychometric analysis of different kinds of learners, and based on a motivational level, many interesting conclusions have been drawn and presented in the result section at the end of the paper. Deep learning model Ludwig Classifier used to calculate, motivational Level is obtained for 100 number of epochs and it is found that the loss is decreasing and in other words, the accuracy of the machine goes on increasing. Each of the categories discussed here has new capabilities, or at the very least expansions of current ones.

1. Introduction

Many aspects of classrooms or learning across the country would be known to our forefathers and mothers: in classroom learning, a teacher speaking to pupils seated in rows of neatly arranged desks; the instructor instructing from a planned lesson, and the learners carefully listening. Since the beginning of the previous century, this conventional learning system has remained virtually unchanged [1]. Learners are divided into classes, grades, and schools, among other hierarchical aggregations. Learners' education is thus predominantly catered to these groups as a one-size-fits-all encounter rather than a personalized and adaptable experience [2]. "the future is already here, it's not very fairly spread," stated science-fiction novelist William Gibson. Gibson mainly refers to the idea that development is merely the expansion of what is unique to something universal and egalitarian in his comment [3]. Ludwig is a deep learning algorithm designed to take advantage of inheritance and code modularity. It was constructed at the level of abstraction mentioned above. Ludwig makes it simpler for practitioners to reuse, extend, and favour best practises in addition to creating deep learning models by only stating their data and tasks.

Unlike the deep learning frameworks that are currently available, which abstract at the tensor operation or layer level, this type-based abstraction enables a higher level of interface. This is accomplished by offering abstract interfaces for every data type, enabling an extension by enabling the creation of any new implementation of the interface. Ludwig is based on the idea of a declarative model specification, which democratises deep learning models by making them accessible to a much larger audience (including non-programmers).

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This may be stated of the current status of learning and evaluation systems. Recent advancements in computing technology have provided us with the means to actualize many previously unrealized inventive ideas [4]. Many of these ground-breaking concepts come from the fields of education, learning, and evaluation. Computation psychology is a new science that lies at the crossroads of several fields. Computational psychometrics is a term that refers to a combination of machine learning algorithms (ML) analytical methods with cutting-edge theoretical psychometric research [5]. Learners' personality assessment researchers have been able to include these methods into the computational psychological assessment model because of advancements in machine learning and big analytics. The algorithmic psychological approach is currently being used in a variety of monitoring and assessment related studies, including cooperative problem-solving, the impact of interpersonal communications on mutuality in economic decisions, and having to learn as we define here [6], [7], using different parameters. Computational psychometrics investigates not just new models for new data types, such as complicated process data, and how such models may be used to integrate or connect various aspects of teaching, learning, and evaluation [8].

In the stages of learning or studying new skills or extending one's talents, learning and assessment are inextricably interwoven [9], [10]. While education and learning are the process through which a person acquires information or abilities, assessment is a method of observing a learner's performance and producing data to conclude what the learner has learned [11]. Effective assessment helps to learn by giving evidence (1) of learners attaining learning goals, (2) to inform teachers' decisions, and (3) to guide future instructions, to name a few examples. The learning system and the evaluation system may have fully autonomous relationships or be tightly related and linked in a feedback loop in which one system feeds information to the other [12], [13]. The Learning and Assessment System is the name given to this combined learning and assessment system (LAS) [14], [15].

Academic achievement and motivation are inextricably linked. It is as vital for educators to identify early age learners' who lack academic interest as it is to identify those who have a high degree of academic motivation. This research aims to build relationships between expected learner academic motivation and their behaviour in the LMS course by looking to create a classification model that can predict learners' engagement based on their behaviour in LMS courses. This study included learners from all ages their motivational level. Three classifiers have been used: artificial neural, decision forests, and svm classifiers. A t-test of the difference in proportions was employed to see whether there is a significant difference in model performance. Despite the fact that all classifiers were successful, the neural network model was shown to be the most effective in detecting learners' engagement depending on their behaviour in the LMS program [16].

By the advancement of ICT then Big Data, a novel educational example consumes emerged, applying ways to successfully comprehend massive amounts of articles and fairy tales, among other things. Even within the same occasion and topic, for example, fresh form kind trainings or pixie stories are flowing out of numerous periods and countries. This research studies suggests a wild having read method machine learning - based to determine the elemental composition of an important storey that have been handed down despite chronological and longitudinal differences that use the form of 72 similar traditional floors of the common fictions "Red Hat" that happen in Europe, Asia, Africa, and elsewhere. Toward accomplish, they use a R language tree and the caret package to conduct research and assess the issues based on the being of multiple forms in a choice tree. We established the reality of the unchangeable fundamental parts of conventional conversations, which are handed down to the restrictions of time and place, as well as the potential of a model that intuitively understands them, via the assessment of the analytical model. These latest results are intended to be secondhand as a novel instructive sector for ICT-based computer rational [17]

The purpose of this education was to assess the present state-owned of the skill in the use of mechanism knowledge in the field of education. Because the number of educations was great, just a few of them were listed in the study's results as good representations. This education demonstrates

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that here are several methods to gain from mechanism knowledge applications in the field of teaching. One of our aims, as indicated in the introductory section, was to try to categorise works in the subject of mechanism knowledge use in teaching. According to our poll, the papers assessed in category A investigate how mechanism knowledge can grade pupils by eliminating human biases A review of research in the B category revealed how machine-learning algorithms may assist schools or faculties in reaching out to students and getting them the aid, they need to be successful as soon as feasible. Many enrollment management methods rely on student retention. It has an impact on university positions, university standing, and monetary stability. Student holding has developed one of the greatest significant concerns for higher education choice creators, hence there are many researches in this area. Assessing research in the C category revealed that the capacity to anticipate student performance is the most significant benefit of machine learning (in terms of the number of studies in scientific databases). By "learning" about each learner, the system can spot flaws and propose strategies to recover. Rendering to our study, this is the most fascinating field of machine learning application for researchers. There have been many researches in this area in recent years, and several machine learning models have been developed to predict student performance on various characteristics.

A review of papers in the D category revealed several examples for how machine learning may assist shift away from standardized testing. Machine learning-based evaluation gives instructors, students, and parents with continuous feedback on how the student learns, the help they require, and the progress they are making toward their learning goals. As previously discovered, research was conducted across numerous relevant databases; however, not all were involved, therefore this might be considered a study constraint. Furthermore, it is possible that some of the relevant research were overlooked by coincidence inside the future, we want to create our own machine learning model for recommending whether or not a potential student should enroll in College Academy algebra, Study of Software Business, founded on several characteristics. Because we have a large database with a lot of info about scholars from prior years, we feel that this education will be useful in assisting our admissionsoffice with the student enrolling process [18].

Overall effectiveness of innovation learning may be boosted by customizing the material and learning tools for each learner, hence maximizing the learning process. Developed in the present Elo-rating algorithm, this study presents a way for measuring content complexity and user knowledge competency. The generated ratings are then utilized in the training process to offer coding activities that attempt to match the user's existing expertise[19]. The proposed technique was tested in an object-oriented training program using a computer tutor platform. The findings indicated that the developed Elo-rating method was effective in proposing coding activities as a proof-of-concept for establishing adaptive and automated valuation of programming projects[20].

The aims of this work were to see if three models could be used to create an efficient categorization model for predicting learners' engagement using college LMS syllabus data as input parameters, and to find the best procedure by evaluating the efficacy of the wonderful addition. The relationship among all potential variables, and then between possible predictors and the target variable, was examined before commencing the simulation model, culminating in a prediction decrease. Several algorithms were utilized to model the data, and all three yielded satisfactory results. The RBF neural network model surpassed the best models developed using the other two methodologies, according to the data[21]. This prototype had a classifier of 76.92 % and used metrics for assessing designs that had shown this model was able to identify all educators for a below degree of education motivation and had the greatest poor outcome of the two other tested models. It had a good positive predictive value but it wasn't the best among the models tested. At a 5% significance level, no variation in efficiency was identified[22].

2. Method

2.1. Computational Psychometrics

Assessment, from a psychometric standpoint, entails inferring what a beginner understands and can do in the actual biosphere based on incomplete information experiential in a standardised

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challenging environment. From the standpoint of knowledge analytics, valuation entails observing practical performance in cardinal knowledge surroundings to determine learner status with the goal of positively influencing the learning process. Although psychometrics and learning analytics have alike aims, such as determinative valuation, they use distinct methodologies and theories to achieve these goals[23]. This also as and integrates the learning analytics and the psychometric assessment approaches in order to pave the path for a more sophisticated knowledge of valuation. We will talk about how to demonstrate this novel way of assessing instructive ideas like thought, motivation, and interpretation understanding abilities, which may be handled using whichever an information method or a hypothesis approach. Finally, we demonstrate that completely new methods of evaluation may be found in the central area anywhere together fields are integrated into a new investigation known as 'Computational Psychometrics.'

The starting point for investigating learning behaviour and consequences is one of the key contrasts between both professions[24]. While the psychometric sector normally takes a top-down strategy, beginning with theory and ending with data collecting, the learning analytics field takes a bottom-up approach, beginning with data investigation and ending with potential higher-level results. The diagram below summarises and contrasts both techniques.

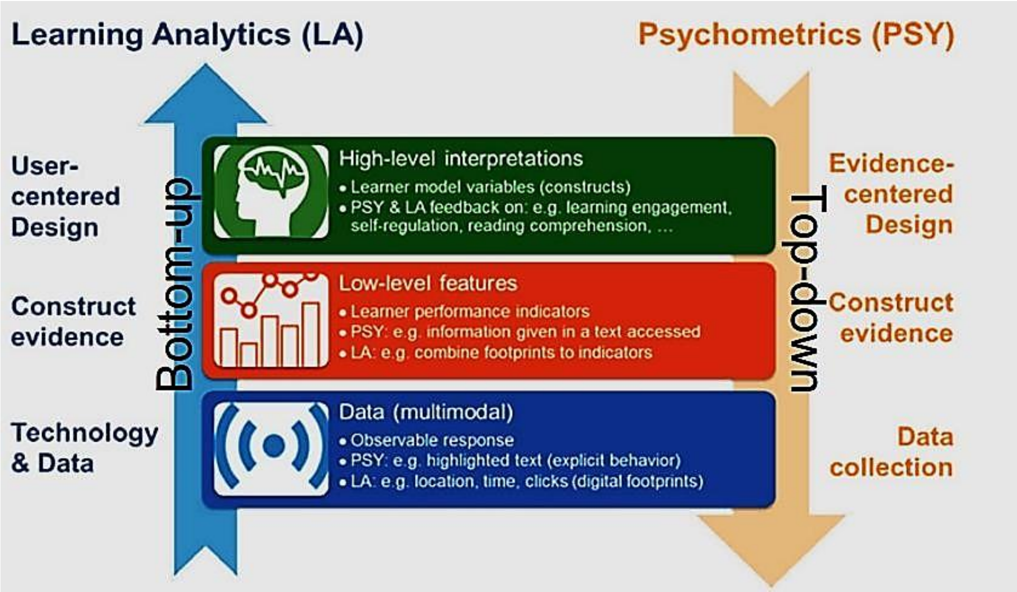

Fig 1. Computational Psychometrics approach

In a digitalized environment, education allows for the observation of real learning behaviour with fine-grained granularity. Next part, demonstrate what is required to make "computational psychometrics available for determinative valuation. Talk about how suggestion statistics and standardised psychological measurements may be utilised to shed light on the learner's knowledge, abilities, and traits while using digital learning environments in higher education[25].

The construction of a digital learning environment that delivers based on detailed helpful for feedback in the training process is a key initial step toward computer personality tests. As a result, the learning environment must assimilate and provision the separate learning procedure with specific knowledge doings rather than just serving as a content management system with lecture slides available for download[26].

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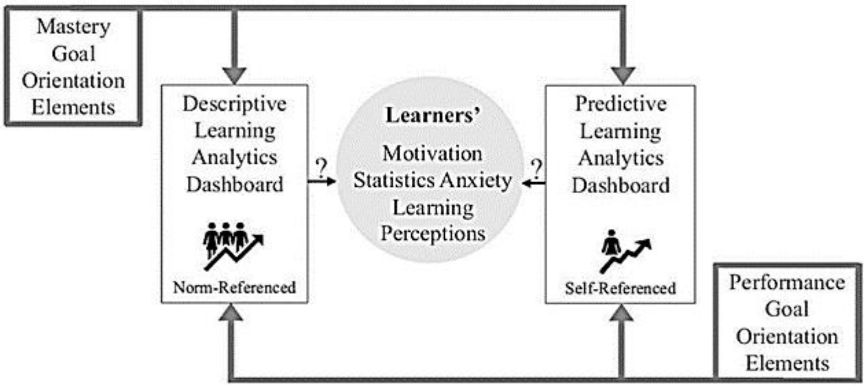

Fig 2. Multiple goal orientation prospective in digital learning

2.2. Model Used

This research studies various parameters like age, gender, and geographical area which is also represented by the differentstates where a person's blog has been used to calculate the motivational level of learners' while learning. The block diagram of the model used to calculate the motivational level is shown in Fig. 3. A detailed primary data has been collected based on questions given below and after considering them a motivational level is calculated[27], [28]. This motivational level further with the help of deep learning is realized as output by considering the effect of all mentioned parameters[29], [30]. The result obtained at the output is then feedback and stored into the database to increase the accuracy of the machine.

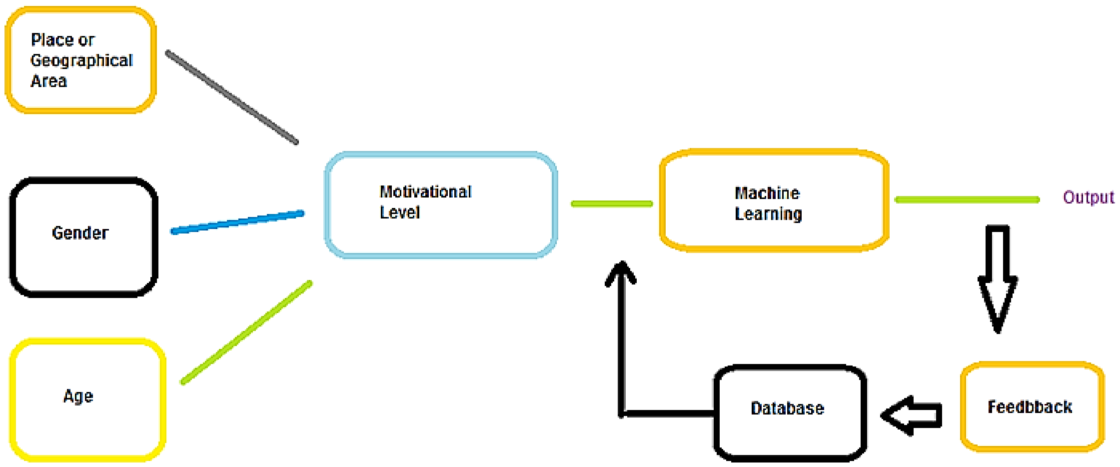

Fig 3. Block Diagram of Methodology Used

3. Results and Discussion

Various questions used in the collection of primary data are given below and after the collection of More than 500 samples. After getting the various responses in the ranges from Strongly Agree (5), Agree (4), Neutral (3), Disagree (2) and Strongly disagree (1) are scored and based on data obtained from the learners a motivational level is calculated[31].

Table 1. Questioners used to collect data

Questions	Description
1.1 Always feel motivated during learning	Learners' feel motivated and positive when theyare learning
1.2 Always spend maximum time learning	Learners' spend more time learning if topics areinteresting

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1.3 Can spend time for learning inspite of a hectic schedule	Learners' spend time learning if topics are interesting even if they are busy
1.4 Must spend time for learning inspite of physical stress	Learners' spend time learning if topics are interesting even if they are tired
1.5 Must spend time for learning inspite of emotional stress	Learners' spend time learning if topics are interesting even if they are mentally disturbed
1.6 Always feel motivated in learning after praying or worshiping	Learners' feel motivated after praying or worship in learning if the topic is interesting and they concentrate more on learning

3. Outcomes Based on Different Parameters

Outcomes received on different parameters such as gender, age and geographical location of learners on the bases of questions mentioned in table 1. Overall 500+ responses received, on the based on different parameters mentioned above, further classification performed Fig shown in table 2.

Table 2. Different parameters and their responses

No.	Parameters	Responses Received
1	Motivational Level in Learners'	527
2	Motivational Level in Females Learners'	232
3	Motivational Level in Males Learners'	295
4	Motivational Level in Delhi & NCR Learners'	356
5	Motivational Level in Outside Delhi Learners'	171
6	Motivational Level in Learners' (Age <=18 Years)	108
7	Motivational Level in Learners' (Age between 19 Years to 22 Years)	239
8	Motivational Level in Learners' (Age between 23 Years to 30 Years)	66
9	Motivational Level in Learners' (Age between 31 Years to 40 Years)	60
10	Motivational Level in Learners' (Age greater than 41 Years)	54

Different types of charts mentioned below on the bases of table 2 data received. Various results after analysis are represented in the form of a Pie Chart in Fig 4.

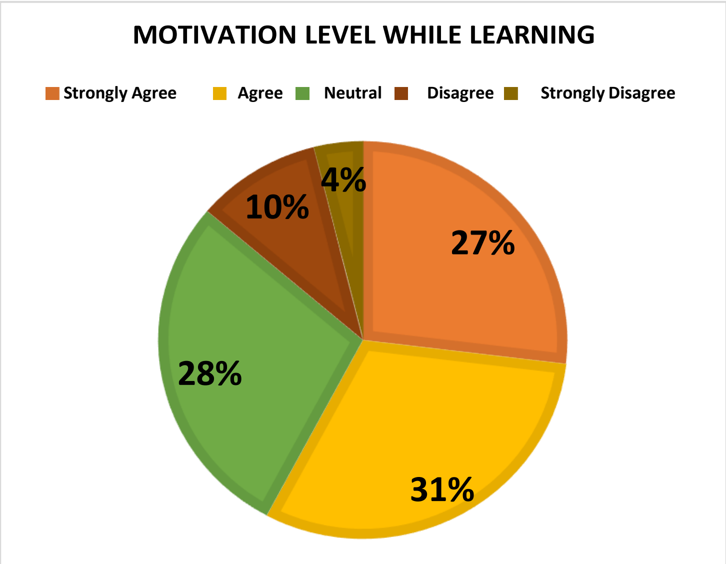

Fig 4. Pie Chart Representation for Calculating Motivational Level While Learning

Inference from Fig 4: Almost 58% of learners agree that, while learning they feel motivated. Whereas 28% of learners are neutral, they may or may not be motivated while learning. It is almost

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1/2 of the agreed percentage. And almost 14% of learners disagree that they are not motivated or feel positive while learning. It is almost 1/4 of the agreed percentage.

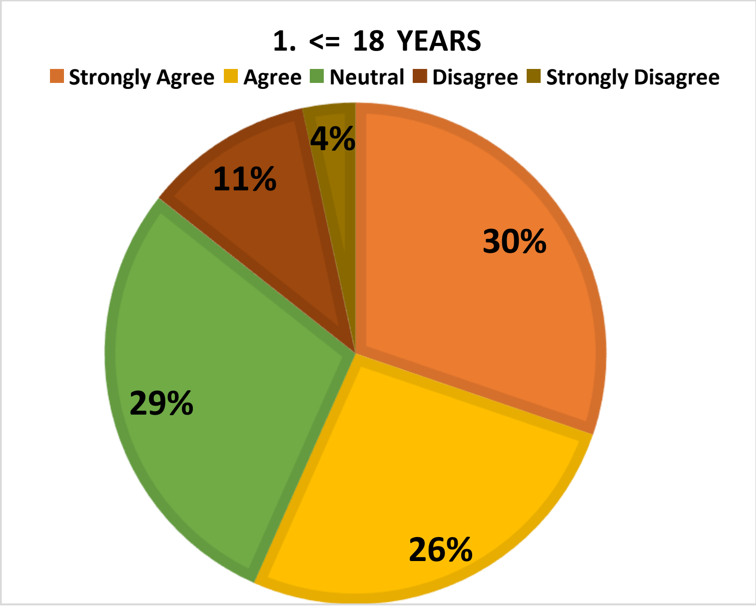

Fig 5. Pie Chart Representation for Calculating Motivational Level While Learning (Age <=18 Years)

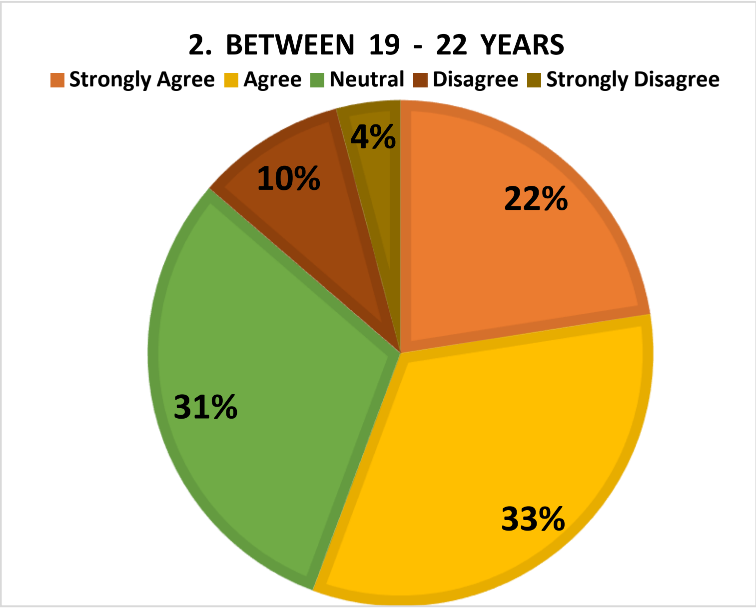

Fig 6. Pie Chart Representation for Calculating Motivational Level While Learning (Age between 19 Years to 22 Years)

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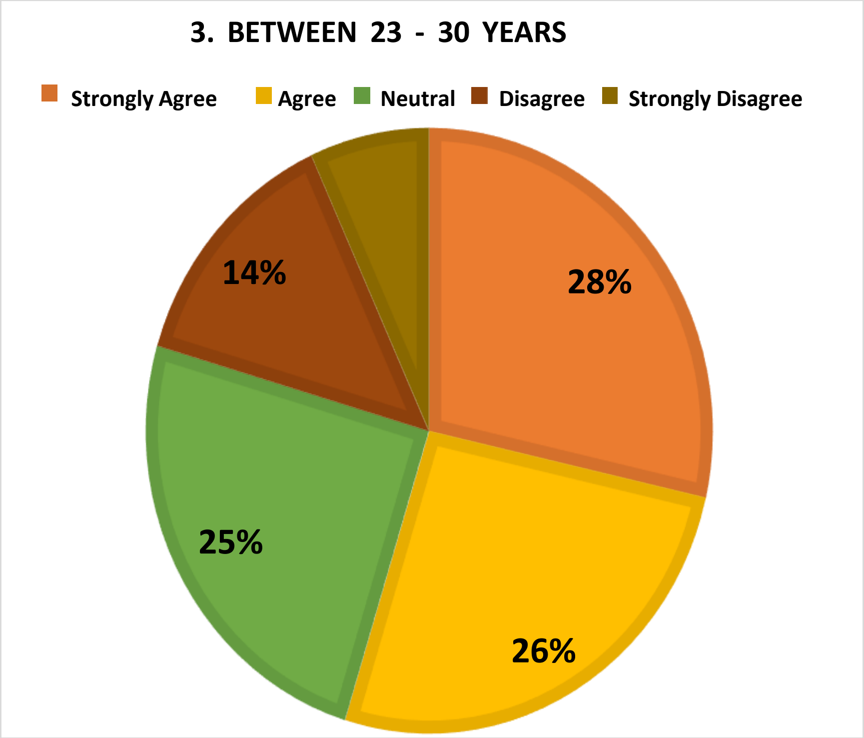

Fig 7. Pie Chart Representation for Calculating Motivational Level While Learning (Age between 23 Years to 30 Years)

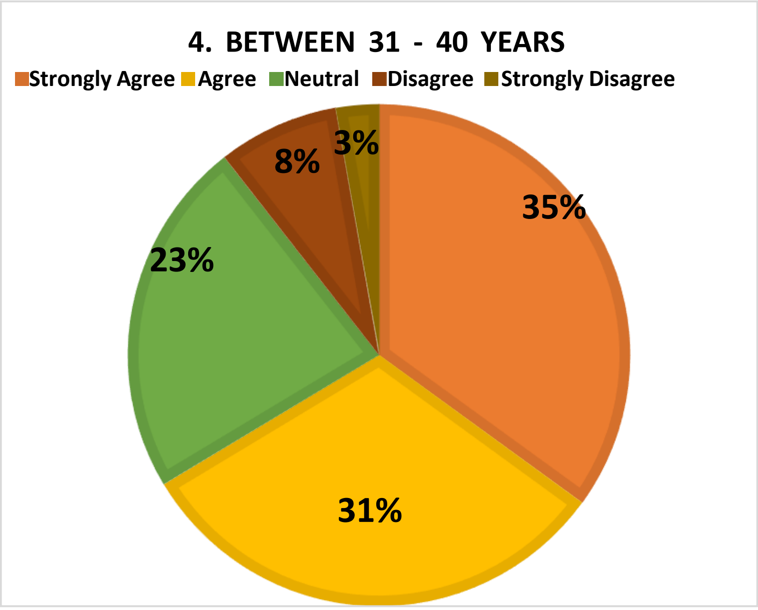

Fig 8. Pie Chart Representation for Calculating Motivational Level While Learning (Age between 31 Years to 40 Years)

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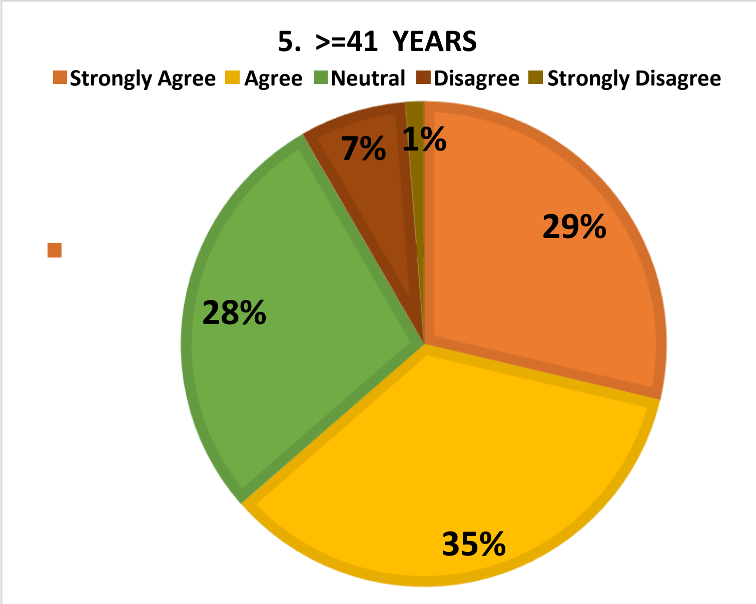

Fig 9. Pie Chart Representation for Calculating Motivational Level While Learning (Age greater than 41 Years)

Inference of above Fig from 5 to 9: In Age-wise above Pie charts, at the early age of learning motivational level is almost 56% of learners agree, 29% are neutral and 15% disagree. But as learners grow and gain experience agree-on percentage increases by 8% i.e. 64%, the neutral percentage is the same i.e. 28%, and disagree percentage decreases to half i.e. 8%. Below Fig 8 is a bar chart represents age wise with values.

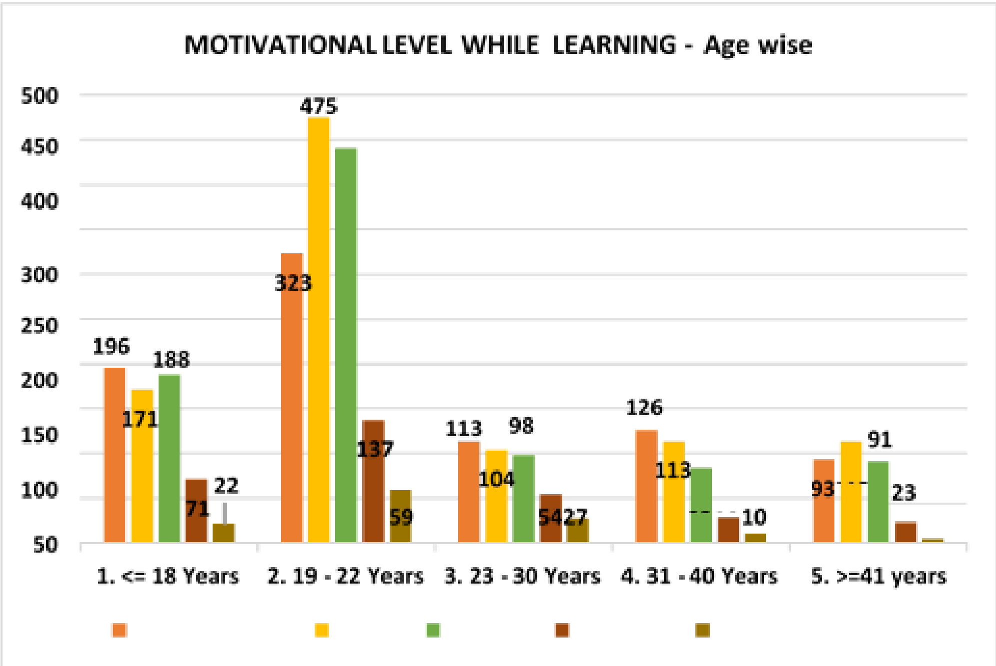

Fig 10. Motivational Level While Learning Considering different age groups

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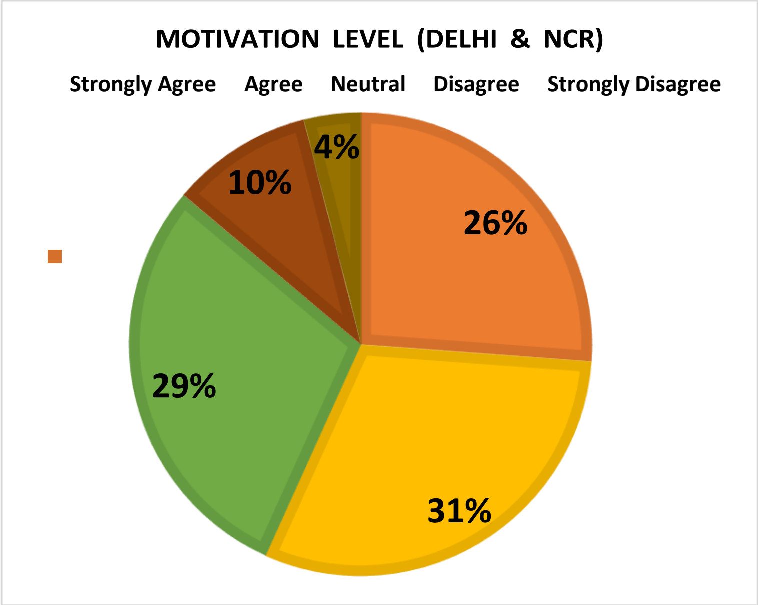

Fig 11. Pie Chart Representation for Calculating Motivational Level While Learning (Delhi & NCR)

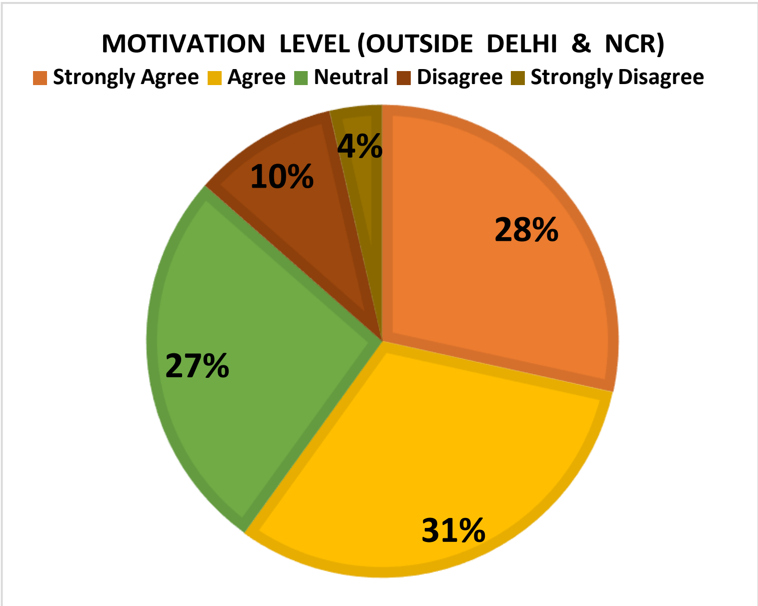

Fig 12. Pie Chart Representation for Calculating Motivational Level While Learning (Outside Delhi & NCR)

Inference of above Fig 10 and 12: In above geographical area wise Pie charts, motivational level is 2% more in outside Delhi & NCR i.e. 59%, as compare in Delhi & NCR i.e. 57%. Disagree percentage is exactly same that is 14%. But neutral percentage is 2% more in Delhi & NCR than outside. Below fig 13 is a bar chart represents age wise with values.

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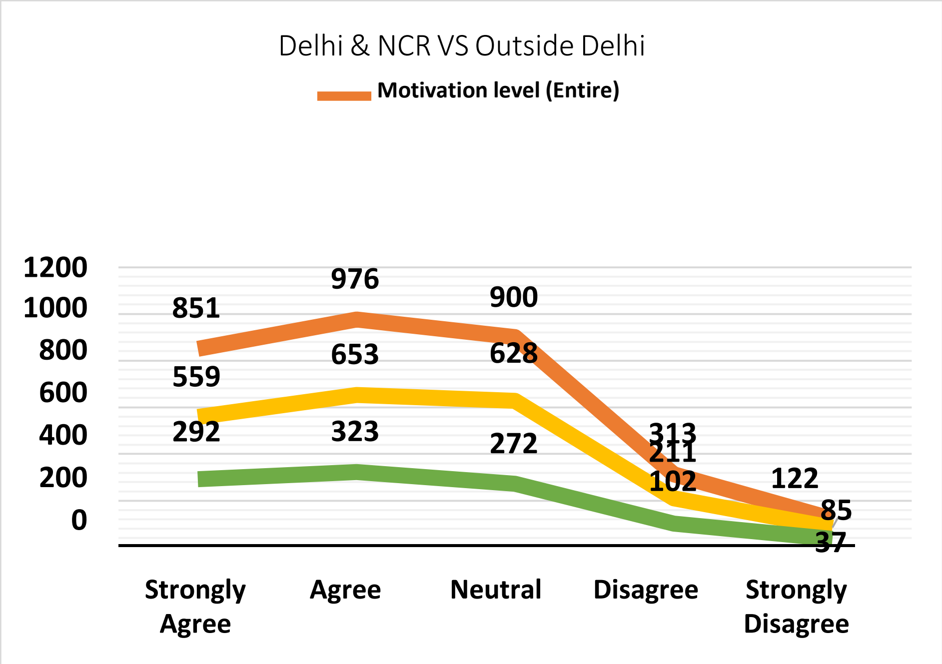

Fig 13. Motivational Level calculation considering geographical region

Inference of above Fig 13: The motivational level is also considered based on the region. From the calculation of motivational level using geographical area wise the line plot is drawn. Agree percentage is 4 times more than disagree percentage irrespective of the area.

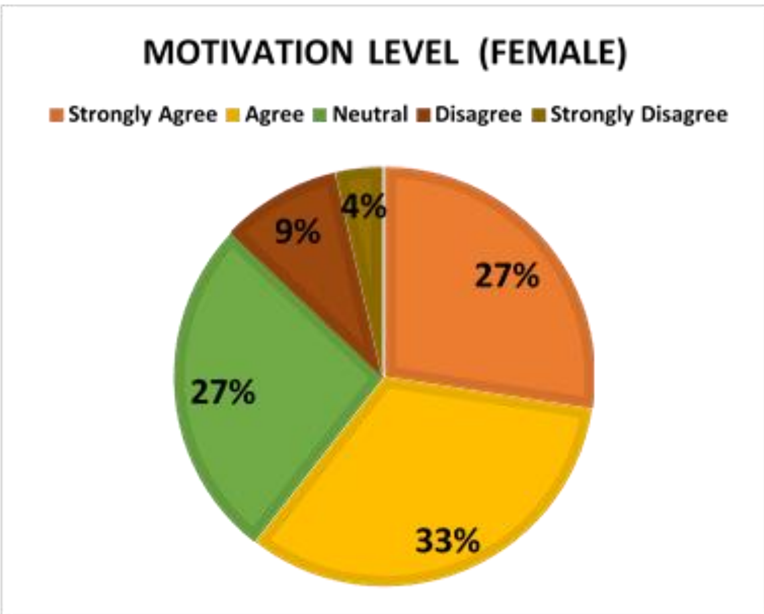

Fig 14. Pie Chart Representation for Calculating Motivational Level While Learning (Female)

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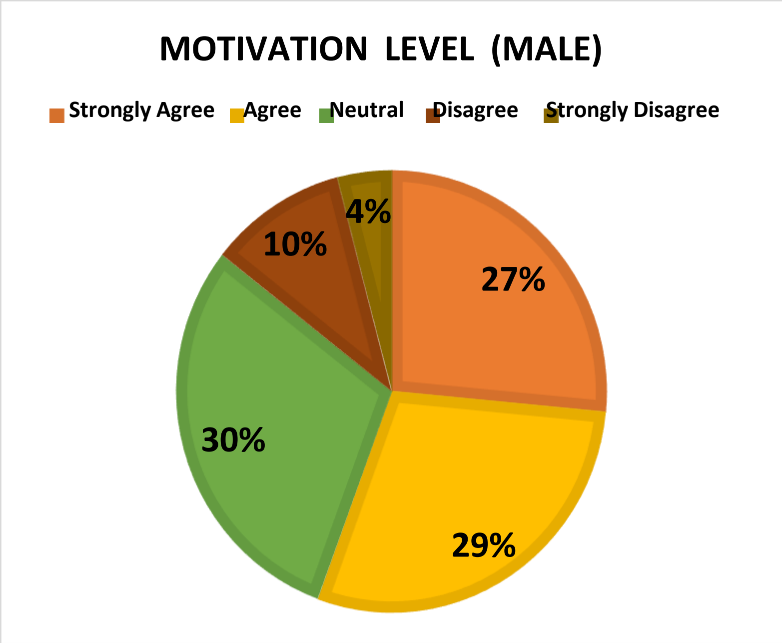

Fig 15. Pie Chart Representation for Calculating Motivational Level While Learning (Male)

Inference of above Fig 14 and 15: In above gender wise Pie charts, motivational level is 4% more in females i.e. 60%, as compare in Males i.e. 56%. Disagree percentage is 1% less in female as compared to males. But neutral percentageis 3% more in males than females.

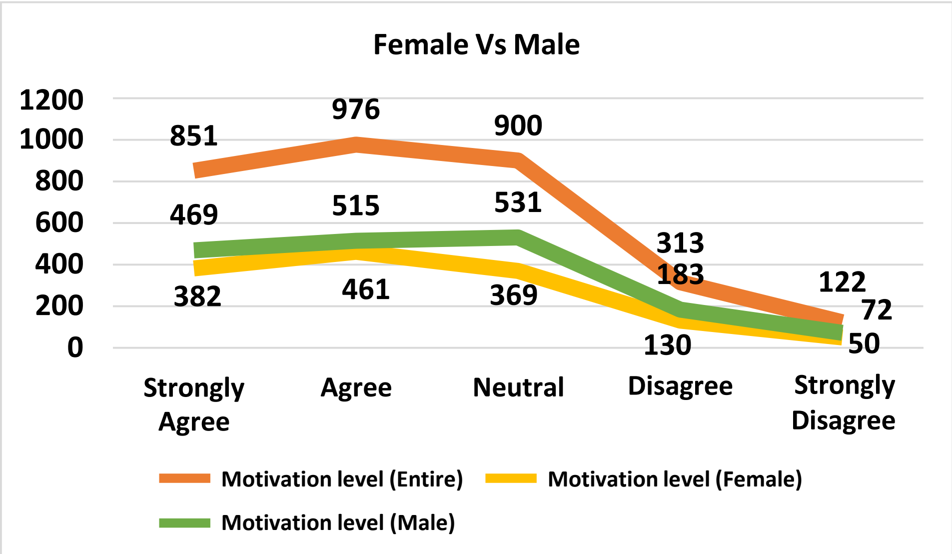

Fig 16. Motivational Level calculation considering gender wise line chart

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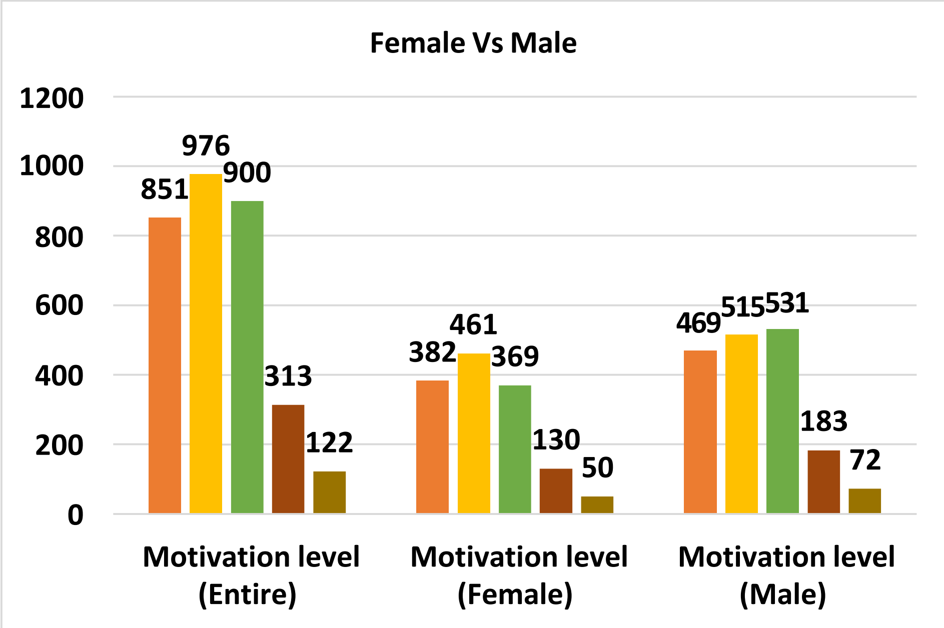

Fig 17. Motivational Level calculation considering gender wise bar chart

Inference of above fig 16 and 17: The motivational level is also considered based on the bases of gender wise. From the calculation of motivational level in males and females, the line plot is drawn shown in fig 14 and bar chart in fig 15 Agree percentage is 4 times more than disagree percentage irrespective of the genders.

Thorough holistic learning and evaluation system in this study, as well as how the computational psychometrics paradigm incorporates all of these complicated components. Motivational level is based on the premise that developing learning, evaluation, and navigation together will improve learners' chances of having a successful, complete educational and learning experience.

7. ML Modelling

Machine learning is an area of AI technology (AI) and computer programming that concentrates on using sophisticated algorithms to mimic the way humans learn, to steadily improve accuracy. Deep learning model Ludwig Classifier used to calculate, motivational Level is obtained for 100 number of epochs and it is found that the loss is decreasing and in other words, the accuracy of the machine goes on increasing. A type-based abstraction is one of the fundamental components that characterize Ludwig. The following data types are supported by Ludwig at this time: binary, numerical (floating-point values), category (unique strings), set of categorical elements, bag of categorical elements, sequence of categorical elements, time series (sequence of numerical elements), text, image, audio (which can also be speech depending on the preprocessing parameters used), date, H3 (a geospatial indexing system), and vector (one dimensional tensor of numerical values). The type-based abstraction makes it easy to add new types. Calculate on the bases of following parameters such as age, educational status, gender, state etc.

```
%%writefile config.yaml
input_features:
    -
        Learner's age
        type: numerical
    -
        Learner's Educational status
        type: numerical
    -
```


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```
        Learner's Gender
        type: numerical
    -
        Learner's state
        type: numerical
    -
        Learning experiences
        type: numerical
    -
        Learner's Highest Education / Learning state
        type: numerical

output_feature:
    -
      name: Motivation Level
      type: numerical
```

Various Headers in the dataset along with the questions are obtained by using df. Column as shown below. Pandas DataFrame is a two-dimensional tabulated data format with labelled axes that is the shape and possibly heterogeneous. Any data point within the dataframe or series can be accessed using the index, which functions like an address. Both rows and columns have indexes; rows' indexes are known as such, while columns' indexes are known as general column names. We frequently use dataframe columns in indexes, which is very easy to analyze. Below are the questions (or columns) which pass in index in both axis for calculation.

```
df.columns

Index(['Timestamp', 'Email Address', 'Learner's Age',
      'Learner's Educational Status', 'Learner's Gender', 'Learner's
       State',
      'Learning Experiences', 'Learner's Highest Education / Learning
       state',
      '1.1 Always feel motivated during learning',
      '1.2 Always spend maximum time for learning',
      '1.3 Can spend time for learning instead of hectic schedule',
      '1.4 Must spend time for learning instead of physical stress',
      '1.5 Must spend time for learning instead of emotional stress',
      '1.6  Always  feel  motivated  in  learning  after  praying  or
       worshiping ']) dtype='object)

y_columns = ['1.1 Always feel motivated during learning',
'1.2 Always spend maximum time for learning',
'1.3 Can spend time for learning instead of hectic schedule',
'1.4 Must spend time for learning instead of physical stress',
'1.5 Must spend time for learning instead of emotional stress',
'1.6 Always feel motivated in learning after praying or worshiping']
```

8. Ludwig Classifier

Deep learning models have shown to be extremely effective in a wide range of machine learning tasks in vision, voice, and language over the previous decade. Ludwig is unusual in its capacity to assist non-experts to grasp deep learning while also enabling faster model improvement iteration cycles for professional machine learning developers and researchers. Experts and researchers may use Ludwig to simplify the prototype process and speed data processing, allowing them to focus on designing deep learning systems rather than data wrangling. The Following Learning Curve For calculating Motivational Level is obtained for 100 number of epochs and it is found that the loss is decreasing and in other words, the accuracy of the machine goes on increasing as shown in the Fig 16.

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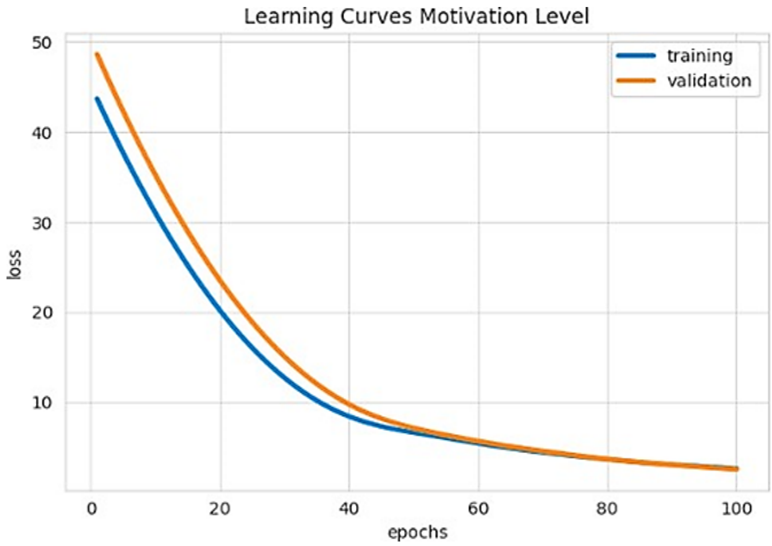

Fig 18. Loss with Number of Epochs learning Curve

After the complete execution of the above code, can view the result. The accuracy at the first and 100th epochs are depicted below. Declarative learning in machine learning through Ludwig classifier was discussed. Ludwig, a set of tools based on deep learning. Because of the toolbox's flexibility, extensibility, and user-friendliness, both experts and novices can train deep learning models, use them to make predictions, and experiment with various architectures. We had a very straightforward use case for this toolbox through this paper.

```
Epoch 100
Training: 100% 3/3 [00:00<00:00, 337.45it/s]
Evaluation train: 100% 3/3 [00:00<00:00, 868.75it/s]
Evaluation vali : 100% 1/1 [00:00<00:00, 973.83it/s]
Evaluation test : 100% 1/1 [00:00<00:00, 872.18it/s]
Took 0.4488s
| Motivation Level | loss   | error  | mean_squared_error | mean_absolute_error |
| train            | 2.6789 | 0.1412 |             2.6789 |              1.2556 |
| vali             | 2.5668 | 0.5090 |             2.5668 |              1.3606 |
| test             | 2.8140 | 0.2091 |             2.8140 |              1.2911 |

| combined | loss   |
| train    | 2.6789 |
| vali     | 2.5668 |
| test     | 2.8140 |
Validation loss on combined improved, model saved

Best validation model epoch: 100
Best validation model loss on validation set combined: 2.5668182373046875
Best validation model loss on test set combined: 2.814007520675659

Finished: experiment_run
Saved to: results/experiment_run
Evaluation: 100% 1/1 [00:00<00:00, 685.01it/s]
```

Fig 19. Result obtained using deep learning

4. Conclusion

Motivational level while learning measured using different parameters, such as gender, age and geographical location of learners. Motivational level in female is more as compared in males, similarly motivational level while learning depends on age, such as at the early age motivational level is high as we are in earning age, it slightly decreases but again increases as we grow older.

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Similarly, motivational level in outside Delhi & NCR is high as compared within Delhi & NCR. Deep learning model Ludwig Classifier used to calculate, motivational Level is obtained for 100 number of epochs and it is found that the loss is decreasing and in other words, the accuracy of the machine goes on increasing. Each of the categories discussed here has new capabilities, or at the very least expansions of current ones. Great progress has been made in the research and innovation of integrated monitoring and assessment systems, additional effort is required to refine the approaches, regularly assess them for fairness, efficacy, and validity, and scale them up. The objective is to be able to give quality educational materials and comments to all learners, regardless of ethnicity or geographic location.

The creation of new forms of flexible study diagnosis models that are suited for learning, as well as the use of artificial intelligence (AI), machine learning and multimodal analytic techniques to improve these psychometric models. While psychometrics is a top-down and theory-driven area, machine learning is a lowest part data-driven study topic. Whereas psychometrics and cognitive analytics target similar goals, such as formative assessment, they are based ondifferent approaches and ideas and are so far significantly divided. The integration of both research fields creates a new research topic called as 'computational psychometrics' at the junction of both professions. In the future years, computational psychometrics will be a major driving force in assessment research and practise. Computational psychometrics may be used in areas such as emotional, motivational, (meta) cognitive, collaborative, and psychomotor learning. By utilising multimodal electronic trace data, it offers up radically new evaluation avenues that might lead to a new input society with non-invasive evaluation.

References

[1] Drachsler, H., &Goldhammer, F. (2020). Learning Analytics and eAssessment—Towards Computational Psychometrics by Combining Psychometrics with Learning Analytics. In Radical Solutions and Learning Analytics (pp. 67-80). Springer, Singapore. https://doi.org/10.1007/978-981-15-4526-9_5

[2] M. Anand, A. Velu, and P. Whig, "Prediction of Loan Behaviour with Machine Learning Models for Secure Banking," Journal of Computer Science and Engineering (JCSE), vol. 3, no. 1, pp. 1–13, 2022. https://doi.org/10.36596/jcse.v3i1.237

[3] Wiswall, M., and Zafar, B. (2015). Determinants of college major choice: identification using an information experiment. Rev. Econ. Stud. 82, 791–824. https://doi.org/10.1093/restud/rdu044

[4] Whitmer, J., Nasiatka, D., and Harfield, T. (2017) "Student interest patterns in learning analytics notifications," in Blackboard Data Science Research Brief, Blackboard Analytics (Washington, DC), 1–14.

[5] A.P. Ambrosio, C. Xavier, F. Georges, Digital ink for cognitive assessment of computational thinking, IEE Frontiers in Education Conference (2015), pp. 1520-1526, https://doi.org/10.1109/FIE.2014.7044237

[6] MacLaren, B., and Koedinger, K. (2002). "When and why does mastery learning work: instructional experiments with act-r "simstudents"," in Intelligent Tutoring Systems, eds S. A. Cerri, G. Gouardères, and F. Paraguaçu (Berlin; Heidelberg: Springer), 355–366. http://dx.doi.org/10.1007/3-540-47987-2_39

[7] C. Angeli, J. Voogt, A. Fluck, M. Webb, M. Cox, J. Malyn-Smith, et al. A K-6 computational thinking curriculum framework: Implications for teacher knowledge Journal of Educational Technology & Society, 19 (3) (2016), pp. 47-57

[8] S. Atmatzidou, S. Demetriadis. Advancing students' computational thinking skills through educational robotics: A study on age and gender relevant differences Robotics and Autonomous Systems, 75 (2016), pp. 661-670. http://dx.doi.org/10.1016/j.robot.2015.10.008

[9] K. Brennan, M. Resnick New frameworks for studying and assessing the development of computational thinking American Educational Research Association Meeting, Vancouver, BC (2012) Canada, 1–25

[10] Von Davier, A. A., Deonovic, B. E., Yudelson, M., Polyak, S., & Woo, A. (2019). Computational psychometrics approach to holistic learning and assessment systems. In Frontiers in Education (Vol. 4, p. 69). Frontiers

[11] Teasley, S. D. (2017). Student facing dashboards: one size fits all? Technol. Knowl. Learn. 22, 377–384. http://dx.doi.org/10.1007/s10758-017-9314-3

[12] F. Buitrago Flórez, R. Casallas, M. Hernández, A. Reyes, S. Restrepo, G. Danies,Changing a generation's way of thinking: Teaching computational thinking through programming Review of Educational research, 87 (4) (2017), pp. 834-860. http://dx.doi.org/10.3102/0034654317710096

http://dx.doi.org/10.36596/jcse.v3i2.529

[13] A. Velu and P. Whig, “Studying the Impact of the COVID Vaccination on the World Using Data Analytics”. Vivekananda Journal of Research, Vol. 10, Issue 1, 147-160.
[14] Mangaroska, K., Vesin, B., & Giannakos, M. (2019, July). Elo-rating method: towards adaptive assessment in e-learning. In 2019 IEEE 19th International Conference on Advanced Learning Technologies (ICALT). Vol. 2161, pp. 380-382. https://doi.org/10.1109/ICALT.2019.00116
[15] C. Cachero, P. Barra, S. Melia, O. Lopez, Impact of programming exposure on the development of computational thinking capabilities: An empirical study IEEE Access, 8 (2020), pp. 72316-72325. https://doi.org/10.1109/ACCESS.2020.2987254
[16] W.K. Campbell, C. Sedikides, Self-threat magnifies the self-serving bias: A meta-analytic integration, Review of General Psychology, 3 (1) (1999), pp. 23-43. https://doi.org/10.1037/1089-2680.3.1.23
[17] M. Cutumisu, C. Adams, C. Lu, A scoping review of empirical research on recent computational thinking assessments Journal of Science Education and Technology, 28 (6) (2019), pp. 651-676. https://doi.org/10.1007/s10956-019-09799-3
[18] J. Del Olmo-Muñoz, R. Cózar-Gutiérrez, J.A. González-Calero Computational thinking through unplugged activities in early years of primary education Computers & Education, 150 (2020). https://doi.org/10.1016/j.compedu.2020.103832
[19] H.Y. Durak, M. Saritepeci, Analysis of the relation between computational thinking skills and various variables with the structural equation model, Computers & Education, 116 (2018), pp. 191-202, https://doi.org/10.1016/j.compedu.2017.09.004
[20] H.B.G. Ganzeboom, P. M. de Graaf, D.J. Treiman, A standard international socio-economic index of occupational status, Social Science Research, 21 (1) (1992), pp. 1-56. https://doi.org/10.1016/0049-089X(92)90017-B
[21] R.M. Gonyea, Self-reported data in institutional research: Review and recommendations, New Directions for Institutional Research (127) (2005), pp. 73-89. https://doi.org/10.1002/ir.156
[22] Pelánek, R. (2017). Bayesian knowledge tracing, logistic models, and beyond: an overview of learner modeling techniques. User Model. User Adapt. Interact. 1–38.
[23] S. Grover, R. Pea, Computational thinking in K-12: A review of the state of the field, Educational Researcher, 42 (1) (2013), pp. 38-43. https://doi.org/10.3102/0013189X12463051
[24] V. S. Grover, R. Pea, S. Cooper, Designing for deeper learning in a blended computer science course for middle school students, Computer Science Education, 25 (2) (2015), pp. 199-237. https://doi.org/10.1080/08993408.2015.1033142
[25] Polyak, S. T., von Davier, A. A., and Peterschmidt, K. (2017). Computational psychometrics for the measurement of collaborative problem solving skills. Front. Psychol. 8:2029. doi: https://doi.org/10.3389/fpsyg.2017.02029
[26] J.F. Hair, J.J. Risher, M. Sarstedt, C.M. Ringle, When to use and how to report the results of PLS-SEM, European Business Review, 31 (1) (2019), pp. 2-24. https://doi.org/10.1108/EBR-11-2018-0203
[27] Von Davier, A. A. (2017). Computational psychometrics in support of collaborative educational assessments. Journal of Educational Measurement, 54(1), 3-11
[28] R. R. Nadikattu, S. M. Mohammad, and P. Whig, “Novel economical social distancing smart device for covid-19,” International Journal of Electrical Engineering and Technology (IJEET), 11(4):204-217, 2020. http://dx.doi.org/10.34218/IJEET.11.4.2020.023
[29] H. Jeon, H. Oh and J. Lee, "Machine Learning based Fast Reading Algorithm for Future ICT based Education," 2018 International Conference on Information and Communication Technology Convergence (ICTC), 2018, pp. 771-775. https://doi.org/10.1109/ICTC.2018.8539447
[30] J.L. Howard, M. Gagné, J.S. Bureau, Testing a continuum structure of self-determined motivation: A meta-analysis, Psychological Bulletin, 143 (12) (2017), pp. 1346-1377. https://doi.org/10.1037/bul0000125
[31] P. Whig, R. R. Nadikattu, and A. Velu, “COVID-19 pandemic analysis using application of AI,” Healthcare Monitoring and Data Analysis Using IoT: Technologies and Applications, p. 1, 2022. http://dx.doi.org/10.1049/PBHE038E_ch1

http://dx.doi.org/10.36596/jcse.v3i2.529