International Journal of Early Childhood Special Education (INT-JECSE)
DOI:10.9756/INTJECSE/V14I5.789 ISSN: 1308-5581 Vol 14, Issue 05 2022

The computer science based teaching strategy on impact of a student knowledge in online learning

Suresh Kallam[1], Chintalacheri Charan Yadav[2],Budideti Vinay Kumar Reddy[3],D Vinay[4]and Devarakonda Venkata Sai Pranav[5]

[1]Professor,CSE,SreeVidyanikethan Engineering College,Tirupati,AP,India.
[2,3,4,5]UG Students ,CSE,SreeVidyanikethan Engineering College,Tirupati,AP,India.
Email [1]:sureshkallam@vidyanikrthan.edu
Email [2] :charanyadav7521@gmail.com
Email [3] :vinaykumar970153@gmail.com
Email [4] :3p1csvec@gmail.com
Email [5] :devarakondapranav066@gmail.com

Abstract
Today's student learning especially in covid time, student learning process is changed to measures the student knowledge using computer science particularly data mining. student knowledge in online learning using use the Jesco strategy as it carries with it considerations that may correspond to the cognitive method followed and in order to achieve positive results and influence the sample directly , Based on the foregoing, the research problem is determined by the following two questions: What is the effectiveness of using the (Jesco) strategy in learning some basic skills in volleyball. Will this strategy affect the level of the sample and are there useful and unhelpful strategies in learning and the aim of the research is to prepare educational units with the Jesco strategy in learning some basic skills in volleyball. Recognize the impact of the Jesco strategy on learning some basic volleyball skills. The researcher assumed that there are statistically significant differences in the tests of some technical skills, before and after for the control and experimental groups. Year. The results of the tests werepresented, the accuracy of the skill of crushing, before and after the sample, analyzed and discussed by means ofdata processing. The researcher reached several conclusions that the use of special exercises on the device de\ signed for the wall by the researcher has a positive effect for the experimental group in Improving the accuracy of the skill of crushing hitting in volleyball and using special exercises, their diversity and gradation, has a clearrole in achieving significant differences betweenthe experimental and control groups in the post tests and infavor of the experimental group. The researchers used the experimental method for its suitability to the nature of the problem, in the manner of the experimental and control groups, and the pre and post tests were conducted. The research community consisted of students of the second stage / College of Physical Education and Sports Sciences / University of Baghdad for the academic year 2021-2022, and their number was (385).As for the research sample, the researcher chose it in a random way in line with the procedures of the research by making a lottery on the people of the second stage students, which numbered (10) people, where three people were chosen and they are (J, M, G) as the researcher chose the division (J) group Experimental (25), and (M) a control group(27), and (G) (15) for the reconnaissance experiment. The researchers also chose the following tests: (crushing, blocking, defending the stadium) After that, they conducted tribal tests and ensured the equivalence of the samples, and then applied the strategy and conducted post tests to obtain the results to be processed statistically toextract and interpret the results. Individual through conclusions, the researchers recommended the need to use the strategy in learning and conduct studies using the strategy and on other samples and other skills.

Keywords: computer based, Machine learning, education, online learning ,teaching strategy.

Introduction

Modern education has undergone substantial changes as a result of the advancement of computer information technology[1]. By bringing new and innovative teaching practices, these innovations have had a significant impact on educational institutions. Students will have a better opportunity to expand their present knowledge [2]and improve in comparison to the traditional school system. Time limits are one of the most difficult difficulties an educator can confront when attempting to meet the needs of each student. A student must have an efficient and successful study approach based on their expertise[3]. Volleyball, like other games[7], depends on basic skills as an important base upon which this game is built toadvance in the level of performance. In an easy and sequential manner, and here emerges the role of the variousstrategies that help in one way or another to simplify it and make it understandable to the learner.Using diverseand effective educational strategies and methods to build and develop their physical and skill abilities and theirmental knowledge, especially the basic skills of volleyball, which need to prepare the player mentally by giving acomplete picture of the technical performance physically and skillfully. If we classify the skills in volleyball intoskills that need to beWork, style, and perhaps new strategies that take into account all aspects that work

DOI:10.9756/INTJECSE/V14I5.789 ISSN: 1308-5581 Vol 14, Issue 05 2022

to learnthe skill, andthroughthe follow-up ofthe researcher,ashe worksin the College ofPhysical Education andSports Sciences[4][13],UniversityofBaghdad,a technicaltrainer.Individualityamong learners,as well as theirenjoyment of several cognitive methods that have a role in the success of the learning process, which promptedthe researcher to use the JISCO strategy as it carries with it considerations that may be compatible with thecognitive method used and in order to achieve positive results and influence the sample directly.Based on theforegoing, the research problem is determined by the following two questions: What is the effectiveness of usingthe(Jesco)strategyinlearningsomebasicskillsinvolleyball.Willthisstrategyaffectthelevelofthesampleandare there useful and unhelpful strategies in learning and the aim of the research is to prepare educational unitswith the Jesco strategy in learning some basic skills in volleyball. Identifying the effect of the Jesco strategy inlearning some basic skills involleyball,and the researchers assumedthat there are statistically significantdifferences between the tribal and post tests for the experimental and control groups in favor of the experimental.Methodandtools:

Figure1:showstheoverallcontributionsofthisdissertationtowardsPOSLS.Greenboxrepresent.

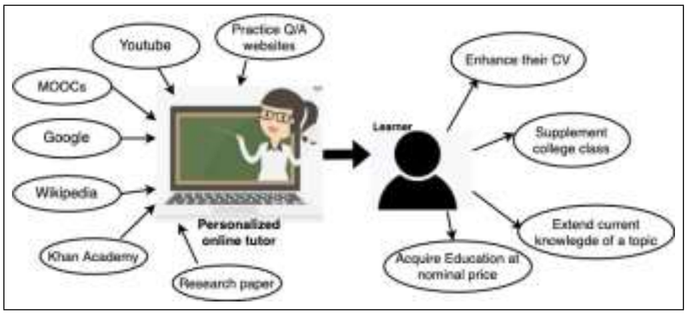

Figure1:Aself-learningtutor

which motivate a person to take up some online course such as, enhancing their CV,supplementing their college education, extend their knowledge of a topic or acquiringknowledge from an institution which they could not afford due to geographical or financial cause[6][8]. The growth of internet has led to spawning of many online course providedby high class institution. However, with more sources of knowledge available, new challengescomeinthescenario.First,itleadstoaninformationoverload[12].

Second,mostof these online learning systems are standard rather than personalized.Since learnerson the online learning system belong to different backgrounds it is important for thesystem to customize based on individual needs.To address these issues, we propose**P**ersonalized**O**nline**S**elf**L**earning**S**ystem(POSLS)thatactsasapersonalizedtutor[9][11].

Table1. ShowsPOSLScapabilitiesandtheirbenefitstolearnersandteachers

POSLS Capability	**Current Research**	**Proposed Research**	**Benefits to learners**	**Benefits to teachers**
Learner Knowledge Assessment	Teachers assess learner mastery .	Knowledge Tracing Model to predict learner mastery.	Inform learners About Their strengths And weaknesses.	Informs teachers About different learners' ability.
Comprehensive Personalized Study Material	Personalized discussion	Develop a comprehensive	Increasesdiscussions,	-

DOI:10.9756/INTJECSE/V14I5.789 ISSN: 1308-5581 Vol 14, Issue 05 2022

Recommendation	Forums Recommendation at an stage early	recommendation of discussion forums based on both student interest in course topics and learner's past forum activities.	Addresses information overload, Questions asked on forums get quick answers, Update of other learner activities on MOOC forums, More engagement.	
ConceptTrajectory	Recommendlist of	Incorporate newtechnologies which specif ically utilize	Addressesinformation	-
Recommendation	concepts to self-learners based on their goal.	data to develop better concept relation prediction techniques.	overload problem.	
Course Navigation Behavior Analysis of learners	Sequentially navigate through the whole course or selectively identify relevant course topics.	Understand learner intent to recommend course topics of interest.	Helps learners navigate through the course.	Help teachers modify the course content sequence to align with popular navigation patterns.

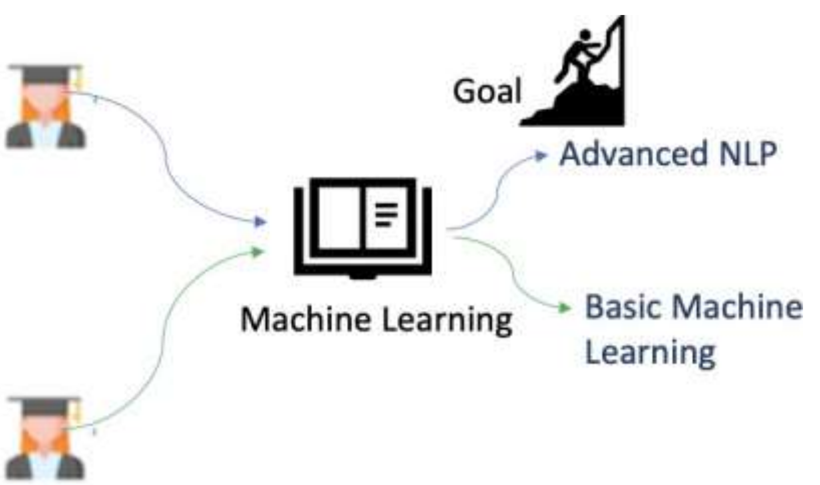

Figure2. AnevaluationoftheStudentswithdifferentgoalsbuttakingthesamecourse

Search Strategy

To conduct this review, several search databases will be used, i.e. IEEE Xplore, GoogleScholar, OneSearch, ACM Digital Library. To find the most related research articles in such databases, it is necessary to identify the appropriate keywords. To do so, an iterative searching process is conducted to filter out the needed keywords that could be used. The related keywords will be refined by combining the keywords from the articles used in each search. By repeating this process, the appropriate search strings for a literature review will be obtained and the resulting search is recorded and shown in the Table 2. To get the latest results, all the articles are filtered allowingonlythosefrom2015to2022.Onlythearticlesthatarefromjournalsandbookswillbeconsidered.

Table 2: Search strings used for study selections referring to each research question ineachdatabase

Research question	Search string	Database

DOI:10.9756/INTJECSE/V14I5.789 ISSN: 1308-5581 Vol 14, Issue 05 2022

RQ1	(((("All Metadata":knowledge definition) OR ("All Meta- data": content knowledge)) AND ("All Metadata":online education)))	IEEE Xplore
	[Abstract: online education] AND [Abstract: knowl- edge] AND [Abstract: content knowledge] AND [Abstract: knowledge definition] AND [Publication Date: (01/01/2015 TO *)]	ACM
	"knowledge definition" OR "content knowledge" OR defi- nition "online education"	GS
	Any field contains online education AND Any field contains knowledge definition	OneSearch
RQ2	((("All Metadata":knowledge management) OR ("All Metadata":automated knowledge extraction) OR ("All Metadata":knowledge measurement)) AND ("All Meta- data":online education) AND ("All Metadata":machine learning))	IEEE Xplore
	[Abstract: online education] AND [Abstract: machine learning] AND [Abstract: knowledge measurement] AND [Publication Date: (01/01/2015 TO *)]	ACM
	"machine learning" "online education" knowledge measure- ment OR management	GS
	Any field contains online education AND Any field contains machine learning	OneSearch

SelectionCriteria

Selecting related work relies mostly on identifying inclusion and exclusion criteria. Theselection criteria decides whether a research article could be used for a specific project.It refines the research process and the strategy of selecting studies following a literaturereviewprocessasdescribedinFigure2.TheselectionprocessisdesignedbasedontheselectioncriteriadescribedbyEmiliePalagietal.ThisprocessisconductedinfourmainstepsasshowninFigure3.

The first step is to perform the search process using the search strategy defined.The search results, especially for the first research question, will give a hugenumberofrelatedarticlessincethesearchkeywordsareconsiderablygeneral.Therefore,this step consists of listing the inclusion and exclusion criteria.The search results willbe ranked by citation number and only the highly cited articles' titles and keywords willbe considered.Furthermore, the articles that are not published in journals or books orbefore 2015 will be excluded.The selection process is shown in Figure 3.If theseconditions are present in the article, the second step will be to assess the titles and abstracts and identify if these articles could contribute to the research.The next step willbe to fully read the selected articles from the search process and assess their quality tocheckwhethertheyarerelatedtothecurrentresearch.Finally,afterafulltextreviewof the selected articles, the ones that showed higher relation to the investigation area ofthis study will be included. Exclusion criteria were defined as follows: articles that aimto predict student's performance (correctly or incorrectly answering questions, passingor not passing an exam) were excluded because we are interested in estimating overallstudent'sknowledgeofspecificknowledgeitemsbasedonthestudent'sresponses.

Table 3. The equivalence of the experimental and control groups, the calculated (t) value, and the

DOI:10.9756/INTJECSE/V14I5.789 ISSN: 1308-5581 Vol 14, Issue 05 2022

statisticalsignificanceofthetribalresearchtests

Reseachquestions	Researchfocus/aim	Contributiontothestudy
RQ1	Application Computer oftec hnologyinOES	OESdefinition
	Applicationofmachinelearn-ingtechniquesinOES	OESandmachinelearning
	Definitionandapplicationofknowledge concepts	Commonconc knowledge epts
	Knowledgemanagement	General knowledge definitions
	KnowledgecomponentsinOES	Students'skillsandperformanceinOES
RQ2	Application of Knowledgetracing methods	Knowledgemeasurement:Knowledge tracing methods,BKT

components, all of them had mentioned skill and performance as key terms when defining students' knowledge in OES. As for the knowledge tracing methods, it has been presented that it is possible to measure specific knowledge units in OES using suitable KT methods. Previous studies that have compared several of these methods indicate that Bayesian Knowledge Tracing (BKT) is the most common and suitable KT method. The acquired results from this literature review showing the common knowledge definition and knowledge tracing method are base for the process of exploratory research as they are used to proceed with this study's implementations.

Exploratory Research Results

The results from the exploratory research contain all information concerning the data files and the implementation's execution results while following the mentioned steps in the planned strategy. This section will present all calculation results of skill, performance, and achievement.

Machine Learning for Skills Measuring

In this section, the skill measurement process will be divided into three main parts respectively showing each result from the evaluation process, the prediction of values, and the cross validation of all data acquired.

Evaluation process

The evaluation process starts by introducing basic statistics on the data acquired from Hypocampus. All steps that were taken during this process and their results after execution of the program will be documented. The data file contained 817213 records in total which described 3300 students' personal information and the 24 specialities available in the system. The data files were very large, that is why the model evaluation was tested using smaller data sets. The first consisted of an evaluation using data concerning all students in the platform taking only one speciality. Therefore, it is necessary to show some statistical information regarding this data in more detail. To check the number of specialities saved in the data along with all the subjects, a test was conducted and the resulting division was recorded.

Asthefirstevaluationwassuccessful,amuchlargerdatasetwastested.ThisevaluationusingtheBKTmodelwasdedicate dtotheentiredataprovidedbyHypocampus.Thelaststepconductedinthisprocesswastoshowalldataconcerningonespecificstudentfora better testing result. Therefore, out of all users, only one student was selected. The selection was only done after all student records were compared. The user with the highestnumberofinteractions(6245records)withthesystemwaspickedforthisevaluationstep.Thestatisticalresultsthatwere providedforeachofthesestepswillhelptheevaluationofthe model using the different metrics .The results of this processwill be represented by a graph that shows each evaluation recorded using the RMSE, theaccuracy,andtheAUCmetrics.

The categorical data in Figure3 acquired from the evaluation processo fallthe

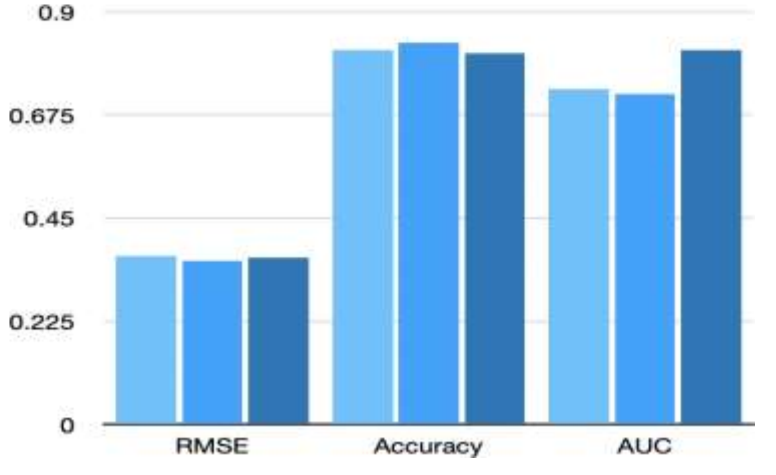

Figure 3: Evaluation of the data using RMSE, Accuracy, and AUC metrics on the selecteddata

steps will be presented with exact measurement numbers and will be further shown anddescribed below table 4.

Table 4: Exact evaluation results from the BKT model using different metrics on theselecteddata

.

	EntireData	Specialty(Cardiology)	Student1
RMSE	0.36	0.35	0.36
Accuracy	0.81	0.83	0.80
AUC	0.73	0.72	0.81

Discussion

After conducting a detailed analysis on the recorded results, it is important to provide adiscussion over all findings of the study while also relating them to the problem formulation. The reliability and validity of these methods along with the ethical considerationsthatwillbefurtherdiscussedhereaswell.Therefore,it is necessary to recall all research questions that were formulated in the beginning ofthe research: (1) How is students' knowledge in OES defined based on the agreed uponknowledge definitions existing in the literature? (2) How is students' knowledge in OESmeasuredbasedonthedataavailableinOESwhileusingthedefinitiondevelopedthroughaliteraturesurvey?

1. As mentioned throughout the study, the first research question highly relies on theliterature review process to give an agreed upon knowledge definition. This method was conducted using a predefined search

and selection strategy to ensure the relevance of all results. During this reviewing process, different knowledge definitions were com- pared and the general concepts extracted from the selected studies were documented as a theoretical background for the study. All the necessary information concerning the knowledge measurement techniques in Hypocampus were also defined. Two types of knowledge, tacit and explicit, were introduced and compared. Whereas tacit knowledge can only be implicit and hard to define, explicit knowledge can be easier to extract and express. This knowledge is used in both tradition and modern education [5]. Compared to how traditional

DOI:10.9756/INTJECSE/V14I5.789 ISSN: 1308-5581 Vol 14, Issue 05 2022

education measures explicit knowledge, the OES as a modern education platform applies a more comprehensive knowledge definition to handle the complex students' activities online. In knowledge was referred to with sub units; skills, performance, and achievement.

Results:

The implementation was strategically planned in three main processes; evaluation, measurement and validation to measure the skill of students. The results from the evaluationprocess targeted three different data sets which respectively described the data from onespecialty, the entire data set, and the data from one specific student. The evaluation wasconducted using three different metrics for each data set.These metrics were mainlyAUC, Accuracy and RMSE. As shown in figure 3, the results of all metrics were veryclose with most data targets. However, it can be noticed that the evaluation result usingAUContheselectedstudentshowedaslightdifference.Itcanbeobservedthatthisnumber was higher than the other data sets. The difference can still be considered minor astheresultingnumbersarestillveryclosesuchasdescribedintable5.2.Thiscanonlybe explained by the differences in students' knowledge mastery. Therefore, this selectedstudentcanrepresentthemajorityofallstudentsusingtheplatform.TheAUCquantifiesthe classification ability of the BKT model that was used for this project. The model canhaveahighperformancewhentheclassifierprovidesareliableoutput[4].TheAUChasa decision threshold of 0.5 and the closer this result is to 1, the better and more reliablethe model's classifier is. As it was previously shown in table 3, the evaluation resultsusing the AUC metric on the selected student is 0.81 which means this BKT model willhave a good performance in later processes. The accuracy metric follows a very similarconcept. According to the study conducted by Badrinath et al. and Pardos et al. pyBKTthis metric also uses a threshold of 0.5 [1][2]. When the result is equal or more thanthis number, the model is considered suitable for the specified data. As shown in the results in table 5.2, the evaluation of the model using the accuracy metric provided resultshigher than the threshold. All evaluations with the different data sets, gave results biggerthan 0.8.This can only explain that the model used will be able to handle all data thatwasacquiredfromHypocampus.ThelastmetricthatwasusedforthisevaluationprocesswasRMSE.Figure3showsthatallr esultsusingthisspecificmetricgaveconsiderablylow values compared to the other previously used ones. RMSE follows a much differentpattern. Values from this metric should be between 0 to 1. When the evaluation result islow and closest to 0 the model can be considered fitting well to the data [3]. Table 2can show that the evaluation results of each data set selected using this metric were allaround 0.3. Consequently, the model is suitable for all data that will be tested in the nextprocessoftheimplementation.

Thenextstepthatwastakenduringtheimplementationwasthemeasurementofthe knowledge of the student's skills using a measured state prediction.The results shownfrom this process were collected from one example student that was specifically pickedfor already explained reasons.As shown in table 3 and 4, while the BKT model isanalyzingeachanswer'sresults,itwasnoticedthatthestudent's

probabilityofansweringcorrectly and their state of knowledge mastery generally increase.For both specialties,the result from the state_prediction and correct_prediction of student 1 went from beingaround 0 to finally closer to 1.However, a small decline can also be observed in theseresults.Thismightbeduetotheprobabilityoftheguessingratementionedinsection .Multiplerecordsforthesamequestioncouldbestoredforonestudent,representingthat a student can answer the same question several times.The answer results may bedifferent each time considering the possibility of guessing and slipping which affects themeasurementresults.

Afterevaluatingthemodelandapplyingthemeasurements,acrossvalidationprocesswasconducted.Thisprocessprovide samorepreciseumbertoverifywhetherthismodelfits the data set or not. It tests and trains the model iteratively. onlytwoitemsareselectedasanexample.Table5.5showsthattheAUCvaluefrombothitemsareveryclosetothenumberobtaine dfromtheevaluationprocess.ThisgivesmorereliabilitytotheBKTmodelthatthisprojectused.

Afterrecordingtheseresultstheperformanceoftheselectedstudentwastobecalculated. This calculation was based on the scores acquired from both selected subjects. Asshown in table 4, for subject 135, out of 44 answered questions, the student only had 7of them incorrect. His performance in this subject was 0.8 which could only mean thattheyhaveperformedwellandmostoftheirquestionswerecorrectlyanswered.However,for item 235, the result recorded was very low (around 0.4) which means the student hasperformed poorly in this subject. Calculating the achievement of this student will be thelast step in this measurement process. The average of how much a student has achievedintheirstudieswillbedependentontheirskillandperformance.Table4showsthatthestudenthasdifferentachievemen tlevelsindifferentsubjects.Thecloserthachievementisto1,thehighertheknowledgemastery.Insubject235,thestudent'sachi evementresultwas 0.9 and in subject 135 it was only around 0.3.This can explain that a student has achieved more in the first subject.

After that, they conducted tribal tests and ensured the equivalence of the samples, and then applied the strategy and conducted post tests to obtain the results to be processed statistically toextract and interpret the results. Individual through conclusions, the researchers recommended the need to use the strategy in learning and conduct studies using the computer science strategy and on other samples and otherskills. Overall student skills are improved and knowledge gained.

Reference

1. M.H.&RapinHabieb.(2010Decembe)..UserConitivemodelforadaptiveinterface.2nd.InternationalconferenceNimes,,r,2010.p.162.France.
2. IqbalAmmarLafta.(2018).Kineticlearningmethodologicalbasics(VolumeOne).Baghdad,Iraq:AhmedPress.
3. Dawood Salman Dawood. (2005). The effect of using the inverse gradient method in the partial method andreciprocallearninginacquiringtheskillsofthesmashhitandtheblockingwallinvolleyball.Baghdad,Iraq:UniversityofBaghdad,CollegeofPhysicalEducation.
4. Abdul-Jabbar Abdul-Razzaq. (1996). A comparative study between the two gradual and reverse methods inteaching the front-handed jump on the jumping horse apparatus. Master Thesis. Mosul, Iraq: University ofMosul,CollegeofPhysicalEducation.
5. NahidaAbdelZeid.(2011).volleyball. Najaf:PrintingHouse
6. Yang, Tzu-Chi, et al. "A two-tier test-based approach to improving students' computer-programming skills in a web-based learning environment." Journal of Educational Technology & Society 18.1 (2015): 198-210.
7. Troussas, Christos, Akrivi Krouska, and Cleo Sgouropoulou. "A novel teaching strategy through adaptive learning activities for computer programming." IEEE Transactions on Education 64.2 (2020): 103-109.
8. M. Ramu , "Study on Potential AI Applications in Childhood Education", International Journal of Early Childhood Special Education, Vol 14, Issue 03 2022.
9. Prasad, P. Y., Prasad, D., Malleswari, D. N., Shetty, M. N., & Gupta, N. Implementation of Machine Learning Based Google Teachable Machine in Early Childhood Education. International Journal of Early Childhood, 14(03), 2022.
10. S. Shiva Prakash," Educating and communicating with deaf learner's using CNN based Sign Language Prediction System, International Journal of Early Childhood Special Education, Vol 14, Issue 02 2022.
11. Ganesh, D., Kumar, M. S., Reddy, M. P. V., Kavitha, S., & Murthy, D. S. Implementation of AI Pop Bots and its allied Applications for Designing Efficient Curriculum in Early Childhood Education. International Journal of Early Childhood, 14(03), 2022.
12. Sushama, C., Arulprakash, P., Kumar, M. S., Ganesh, D., & Sujatha, K. The Future of Education: Artificial Intelligence based Remote Learning. International Journal of Early Childhood, 14(03), 2022.
13. Babitha, M. M., Sushama, C., Gudivada, V. K., Kazi, K. S. L., & Bandaru, S. R. (2022). Trends of Artificial Intelligence for Online Exams in Education. International Journal of Early Childhood, (01), 2457-2463.