Capturing Latent Learning Indicators Through Technology: New Paradigms for Measuring Student Learning

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Abstract

Context

Technology has been helpful in the field of education for the design, delivery, and assessment of courses. Though academicians quickly adopted the new technology for delivery, they still use the traditional written exams to assess student learning, even in professional courses, including medical, engineering, yoga, and music education systems.

Purpose

The paper focuses on the investigation of how recent technological advancements help capture the hidden and accurate learning indicators of student learning, what devices are found helpful by researchers towards capturing the latent learning indicators, what the trends are, and what are the publicly available datasets that can catalyze the research in the field of learning analytics.

Methods

The study was carried out by adopting the PRISMA template of Systematic Literature Review (SLR), and the four phases, including identification, screening, selection, and inclusion methods, were carried out towards investigating the research questions.

Outcomes

This paper helps academicians and researchers in the field of education and learning analytics to get an overview of the current trend and identify the research gaps towards integrating data from multiple sources and connecting the educational theories with the captured parameters.

Conclusion

A drift has been observed from unimodal data sources to multimodal sources, capturing the data from the perceived behavior of the student to the hidden cognitive and affective domain characteristics.

***Keywords*—**Learning analytics, Cognitive domain, Affective domain, Diagnostic analytics, Predictive analytics, Prescriptive analytics.

I. Motivation

STUDENT'S learning is often measured through formative and summative assessments, which are majorly in time-bound written exams, even in professional courses like medicine, engineering, fashion technology, yoga, and music education. Despite several pedagogical initiatives like Project- Based Learning (PBL) (Mallibhat et al., 2022), Problem-Based Learning (Wood, 2003), Activity-Based Learning (Sharma et al., 2018), and Blended Learning (Vijaylakshmi et al., 2021) methods listed in the literature, in the majority of the assessment occasions, students are assessed through written exams, which may not be the reflection of the actual competencies and skills acquired by students. The problem of assessing students' learning through written exams has drawbacks, including the ability of the student to comprehend the learnings within a given time, language constraints, and the nature of the written exams emphasizing rote learning (Condon & Kelly-Riley, 2004) The problem is much more significant in non-native English-speaking countries like India.

On the other hand, Technology Enabled Learning Environments (TELE) are rapidly expanding, especially in the post-pandemic age, to meet the needs of millennial and Gen-Z learners. These TELEs can record students' digital footprints, which aids teachers in assessing students learning.

The limitations of traditional assessment systems and the advantages of TELE motivated the authors to carry out the Systematic Literature Review (SLR) to understand the existing body of knowledge and identify the research gaps towards capturing learning indicators through technology. This study helped the first author crystallize the doctoral degree's research questions and objectives.

II. Introduction

Intelligent Computer Assisted Instruction (ICAI) was first used in 1960 to collect student log data to analyze the student's learning patterns. However, a new area of study known as "Learning Analytics" has evolved in recent years as a result of the confluence of "learning," "analytics," and "human-centered design." Learning analytics is a topic of research that deals with acquiring, measuring, analyzing, and reporting information on students, learning environments, and their surroundings, according to the Society for Learning Analytics Research

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(SoLAR). The growth of technology has catalyzed learning analytics research and provides capabilities to capture data much beyond log data.

Learning analytics has categories, including descriptive, diagnostic, predictive, prescriptive, adaptive, and causal analytics.

Descriptive analytics, often known as dashboard analytics, is the most fundamental type of data analysis and focuses on identifying trends from historical and present data. This type of analytics investigates the answers to the question, "What happened?"

Diagnostic analytics[1] is used to analyze data to identify the factors behind trends and variable correlations. This progressive descriptive analytics and analysis step can be carried out manually, algorithmically, or through statistical tools. This type of analytics investigates answers to the question, "Why did this happen?"

The use of data to forecast upcoming trends and occurrences is known as predictive analytics. It projects prospective future situations using historical data to guide strategic decision-making. Regression analysis is one of the most widely used predictive analytical tools. It investigates the answer to the question, “What might happen in the future?”

The technique of analyzing data to decide on the best course of action is known as prescriptive analytics. Considering all relevant factors, this analysis produces recommendations for the subsequent stages. Prescriptive analytics is a valuable technique for making data-driven decisions.

Predictive and prescriptive analytics are integrated to make real-time adjustments in adaptive learning analytics, while predictive and diagnostic analytics are integrated to understand the cause-and-effect relationship in causal analytics methods.

TELEs offer a wide range of data capturing facilities (how to capture); however, 'what to capture,' 'when to capture,' 'why to capture,' and 'what information do they convey are grounded in the learning theories. This paper tries to bridge the gap by investigating the following research questions.

1. How technology-enabled data sources are capturing the latent learning indicators of the student?
2. What devices and software are the state of the art that enables the capture of latent learning indicators of the student?
3. What type of analytics is currently the state of the art?
4. What data sets are currently available that can help to build a machine learning/deep learning model for predictive and prescriptive analytics?

To investigate the research questions, the authors found that there needs to be a comprehensive literature review that can address the above research questions. This motivated the authors to perform the Systematic Literature Review (SLR).

The SLR process using the PRISMA method is described in Section II; Section III discusses the findings concerning each of the research questions, followed by inferences in Section IV.

[1] https://online.hbs.edu/blog/post/diagnostic-analytics

III. SYSTEMATIC LITERATURE REVIEW (SLR) PROCESS

The objective of SLR is to examine, summarize, and "reconcile the evidence to inform research policy and practice." (Petticrew &Roberts, 2006). Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) data flow method was adopted (Moher et al., 2009; Page et al., 2021), and the flow consists of four phases: identification, screening, selection, and inclusion. The entire flow diagram is shown in Figure 1.

A. Identification

The process of SLR began with the identification of keywords and databases. An exploratory way of searching was used on Google Scholar to identify the initial keywords. Databases, including IEEE, Science Direct, Google Scholar, ACM, and Scopus, were considered to find the relevant papers. In addition to this, to address the fourth research question, author had to search for data bases including Kaggle and papers with code and found additional papers.

The keywords used to find the appropriate papers are smart learning environments, learning management systems, and student learning. Advanced search options in the databases were used to select the year of publication. Duration from 2003 to 2023 was used to identify the papers. 219 papers were identified, including 115 conference papers and 104 journal articles. 18 papers were removed during the elimination of duplicates.

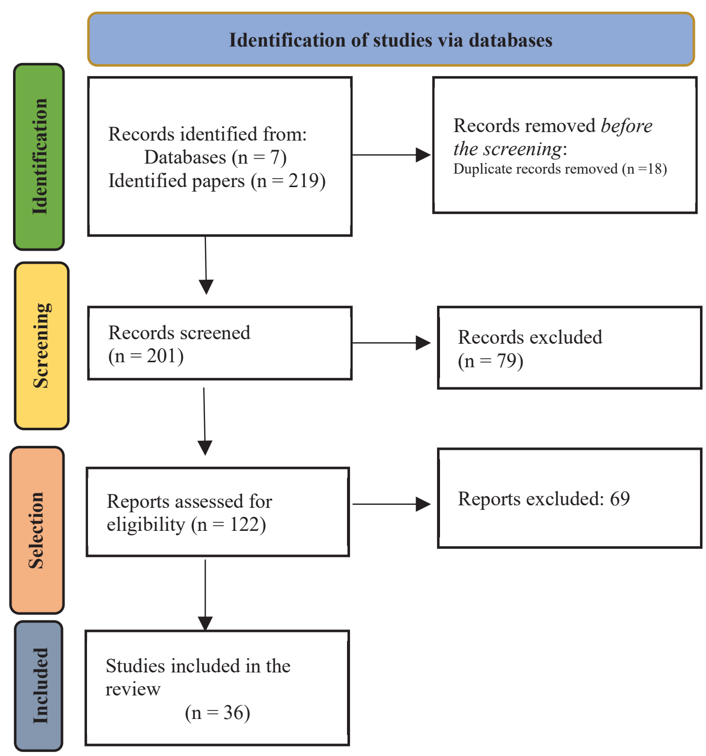

FIGURE 1 PRISMA FLOW DIAGRAM USED TO CARRY OUT SLR

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B. Screening

Screening criteria -year (exclusion criteria- E1) was used to identify papers, while the other exclusion criteria included E2- Short papers/ papers with only abstracts. E3- Non-English papers, E4- Only conceptual works. Inclusion criteria I1- Papers from early access, I2- papers related to Educational Data Mining were also considered. I3- Primary source articles and secondary source articles were also considered.

C. Selection and Inclusion

A total of 122 articles were selected and passed for round 1 and tried categorizing the papers into three categories: strongly selected category, weakly selected category, and reject category. There were 19 papers in the strongly selected category and 34 papers in the weakly selected category. All the secondary search articles were categorized into weakly selected categories, while 69 papers were classified into the reject category. The papers where only qualitative analysis was carried out based on focus group discussions or surveys without technology were excluded from the study as it is beyond the scope of the paper. Finally, 36 papers were shortlisted for the following study.

IV. Literature summary

SLR was carried on with the lenses of formulated research questions. The subsections summarize the literature about each of the research questions.

A. How technology-enabled data sources are capturing the latent learning indicators of the student?

Technology has enabled data capture both in in-classroom (formal learning setting) and online (in-formal learning settings) environments.

The data obtained from the in-classroom environment enables to capture the data related to student's behavioral activities (physical domain), including attendance (Bhattacharya et al., 2018), (Chango et al.,2021) posture (Henderson et al., 2020), body movements (Ashwin et al., 2023), yawning (sleepy) (Omidyeganeh et al., 2016) interaction with peers (Liu et.al., 2019) interaction with teachers (Liu et.al., 2019), detection of malpractices (Prathish, S., & Bijlani, K, 2016)

On the other hand, the data from the online settings enables the capture of student data beyond behavior characteristics and extends to the cognitive and affective domains. Figure 2 shows the tree diagram representing various data sources in formal and informal learning settings.

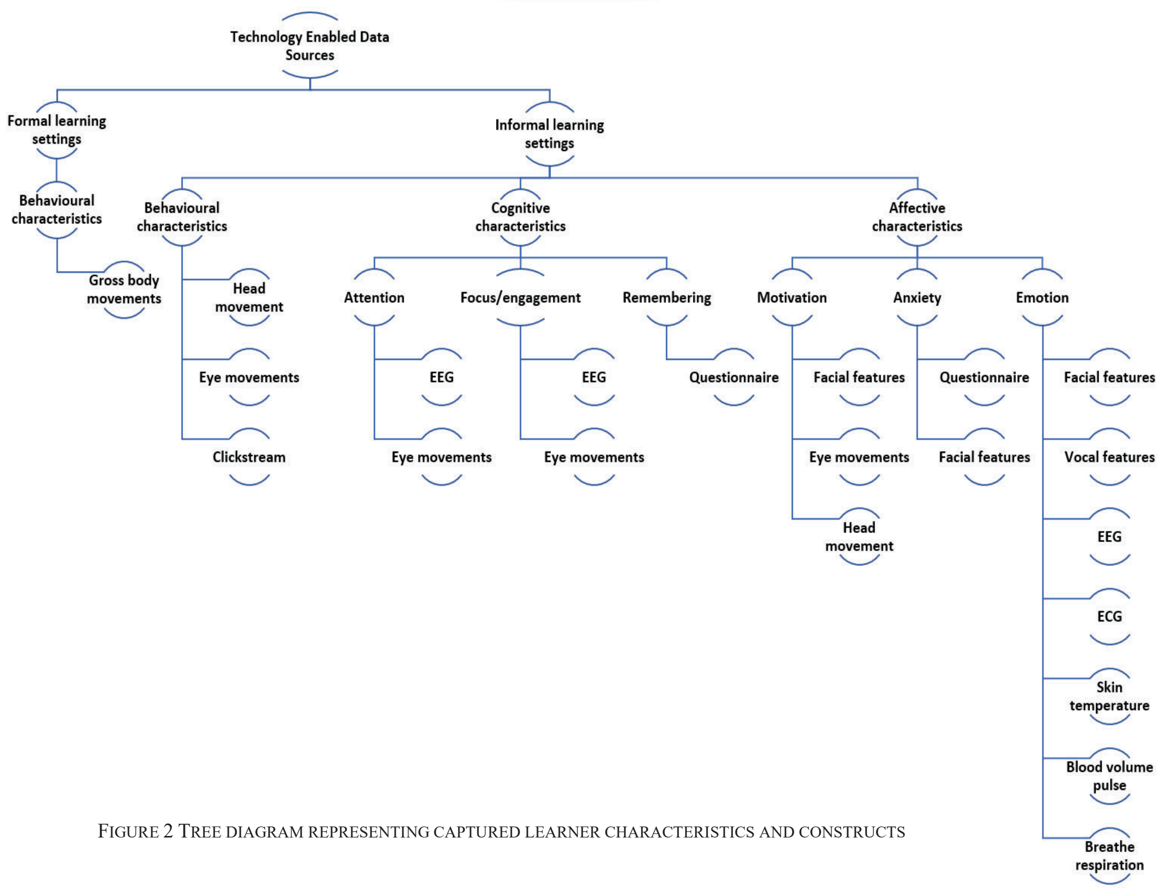

Figure 2 Tree diagram representing captured learner characteristics and constructs

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The branches of the tree diagram represent the characteristics captured, and at the next level of the tree, the measured construct is shown, and the leaf node represents the data source.

Each of the constructs is measured through a set of parameters, which serve as learning indicators. Table 1 shows the constructs' mapping, with measured parameters and the learning indicators.

The breadth of the literature has spread in different dimensions. Another dimension of literature is the data sources based on the space from which the data is captured (Mu, S et.al., 2020). The data spaces are classified into digital, physical, physiological, psychometric, and environmental spaces.

Physical space refers to the data space that captures the learner's behavioral characteristics, including gestures and gross body movements, captured through sensors and cameras. Digital space refers to the data space that captures the digital footprints of the learner during the learning process.

While the learner is engaged in learning, the learner exhibits several physiological changes that convey information about the amount of learning. This data space refers to physiological space.

Psychometric space refers to the data captured through surveys or questionnaires that can serve as feedback on learning from the learners. It can be captured using technology like Mentimeter[1], Google Forms, LMS-based survey forms, or pop-up questions while using the instructional material.

Environmental space refers to the data related to the environmental parameters like temperature and weather conditions affecting the learning.

The data from each of the mentioned spaces is a rich source of information about the learner and the learning. The data can exist in either time series data, including sensor data, video, textual data, or in the form of images click stream data.

Researchers have used multiple hardware software to capture various forms of data and used data from multiple sources to draw inferences about the learner and the learning.

B. What devices and software are the state of the art that enables the capture of latent learning indicators of the student?

Technological advancement has enabled us with multiple hardware and software that help capture the learning indicators. One of the challenges that a researcher faces is choosing the appropriate hardware and software for the data capture. Appropriate hardware and software can orient the researcher and reduce the efforts during data collection. Thus, a table summarizing the various tools and techniques used by researchers to capture learning indicators in formal and informal learning settings is shown in Table 1.

[1] https://www.mentimeter.com/
[2] https://www.mendeley.com/datasets
[3] https://www.cmu.edu/datalab/tools/datashop.html
[4] https://dataverse.harvard.edu/

C. What are the trends and types of analytics currently being used?

Following are the observations by the authors in the direction of investigating the trends and types of analytics currently being used. The summary is represented in Figure 3.

1. Predictive analysis techniques are becoming more popular than descriptive analysis techniques.
2. Methods for prescriptive, adaptive analytics are still in the development stage or not integrated with the existing systems.
3. The transition from unimodal to multimodal sources of information has also been noted as a trend.
4. The information is combined at the characteristics level (for example, behavioral characteristics with cognitive characteristics, cognitive characteristics with affective characteristics), construct level (for example, attention with gross body movements), and feature level (for example, blink rate with pupil diameter).

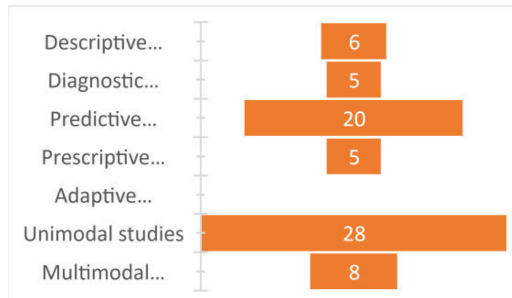

FIGURE 3 TYPES AND TRENDS OF ANALYTICS

D. What data sets are currently available that can help to build a machine learning/deep learning model for predictive and prescriptive analytics?

Among 36 papers included in the study, only 9 papers presented the data set description. As a result, the first author had to search for the datasets through papers and platforms like Kaggle, Papers with code towards addressing the fourth research question.

The authors found three types of datasets, namely.

1. Data sets are released by organizations/ research labs to facilitate the other researchers to carry out the research. It included Mendeley data repository[2], Carnegie Mellon University's DataShop and DataLab[3], Harvard dataverse[4]. These datasets are publicly available.
2. Data sets using crowd-sourced platforms and as a part of Educational Data Mining (EDM) conferences. These datasets are part of hackathons and made available on platforms, including Kaggle and Papers with code. These datasets are publicly available, along with associated research papers and code.
3. Data sets are released by individual researchers. The associated datasets may be made available to researchers upon request. Table II shows the summary of such available datasets.

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TABLE I
SUMMARY SHOWING THE VARIOUS HARDWARE AND SOFTWARE USED TO CAPTURE DIFFERENT CONSTRUCTS

Context of the studies	Construct	Parameters (Operationalized through)	Hardware and software used	Indicator/feature	References
Learners' attention detection, Cognitive profiling of learners, Quantification of user engagement, Mind wandering study, Drowsiness detection	Attention	Eye movements	i-Trace, Tobii eye trackers with Tobii pro lab software, Webcams	Eye fixations, saccades, pupil position, gaze vector	Anwar et.al., 2021 Grandchamp et.al., 2014 Olsen et.al., 2022 Sharif et.al., 2019 Wang et.al., 2021 Wong et.al., 2023,
		EEG	Emotiv, NeuroSky MindWave Mobile BrainWave Starter Kit, Brain Vision, Ant Neuro, BrainVision actiCamp with BrainVision PyCorder, Open BCI, MATLAB with EEGLAB, BCILAB and ERPLAB	Frequency bands, Event-Related Potentials (ERP), power spectral density, coherence values	Baker et.al., 2010 Chakladar et.al., 2021 Hassan et.al., 2020 LaRocco et.al., 2020 Li, X et.al., 2011 Souza et.al., 2021 Toa et.al., 2021
		Eye movements and EEG	Wearable eye trackers NeuroSky MindWave Mobile BrainWave Starter Kit	Pupil movement, Frequency bands, Event-Related Potentials (ERP)	Khosravi et.al., 2022 Lai et.al., 2019
Determining the effectiveness of instructional resources, Student thought patterns and reading behaviors	Engagement, attention (focused and instantaneous), working memory, and visual perception	EEG	14-channel Emotiv EEG device	Statistical features, including minimum, maximum, mean from the time domain, and average power and power of alpha, beta, and gamma, were captured.	Benitez et.al., 2016 Masood et.al., 2017
	Engagement	EEG, Eye movements, heart rate variability, Galvanic Skin Resistance	Muse	alpha, beta, and gamma absolute band power, eye gaze coordinates, eye motion velocity, inter-beat interval (R-R), skin conductance value	Giannakos et.al., 2020 Hussain et al., 2011 Krigolson et.al., 2017
		Click patterns participation in discussions.	Moodle-based LMS, Vimeo, YouTube	Time spent on tasks; number of tasks/milestones completed	Botelho et.al., 2019 Brodny,2017, Joshi et.al., 2022, Yue et.al., 2019
		Eye movements(gaze)	Webcam and Webgazer	Area of Interest (AOI) and off-screen proportions	Yang et.al., 2021, Papoutsaki et.al., 2015
Malpractice detection	Engagement	Facial features, open/ closed eyes, head movement, object detection, hand signs	Webcam, microphone, OpenCV	Facial key points, hand key points	Hussain et al., 2011, Prathish, S., & Bijlani, K, 2016
Student engagement with the video content	Remembering	Questionnaire	H5P tool	Response from the learner, time taken to give a response, number of attempts taken to give the correct answer	Amashi et.al., 2021 Amashi et.al., 2023
Dance tutoring system, yoga studies, Student interaction with teachers and peers	Gross Body Movements, head movements, hand gestures	Posture	Kinect, RGB camera, Myo, Real sense	Power and wavelength of the reflected light	Ashwin et.al., 2023 Henderson et al., 2019
Emotional meter	Engagement	EEG, Eye movements	SMI eye-tracking glasses	Pupil diameter, blink rate	Mele et.al., 2012 Zheng et.al., 2018
Understanding the learner experience through multimodal data	Attention + Engagement	EEG, ECG, BVP,	Eye tracker, Empatica E4 wristband, 20-channel EEG machine, webcam	Blood volume pressure, heart rate, body temperature. Keystrokes, facial key points	Monkaresi et.al., 2016, Villarroel et.al., 2018

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TABLE II
SUMMARY SHOWING THE VARIOUS AVAILABLE DATA SETS ALONG WITH CAPTURED CHARACTERISTICS, DATA SPACES, AND LINKS TO ACCESS THE DATASETS

Name of the dataset	Dataset description	Characteristics captured	Data Space	Link for the dataset
Stanford University's Social Network: MOOC User Action Dataset	The user activities on a well-known MOOC platform are represented by the MOOC user action dataset. The actions are shown as a directed temporal network. Edges reflect user actions on targets, whereas nodes represent users and course activities (targets). The actions contain timestamps and properties.	Behavioral (Clickstream)	Digital space	act-mooc.tar.gz
Carnegie Mellon University's DataShop and DataLab	Holds 358,000 student records from online courses, intelligent tutors, simulators, and educational games, totaling more than 705,000 hours of student data spread among 1466 datasets.	Behavioral (Clickstream)	Digital space	https://www.cmu.edu/datalab/tools/datashop.html
Open University Learning Analytics dataset	It includes information for seven courses on the Virtual Learning Environment (VLE), students, and their interactions with it.	Behavioral (Clickstream)	Digital space	https://analyse.kmi.open.ac.uk/open_dataset
NUS Multi-Sensor Presentation (NUSMSP) Dataset	It comprises four different categories of data: educational data, sensor data, EMA data, and pre-and post-survey replies.	Behavioral + Affective	Physiological, Digital, and Psychometric space	https://studentlife.cs.dartmouth.edu/dataset.html
EdNet	Santa, a multiplatform AI tutoring service with more than 780K users, has aggregated all student-system interactions into a dataset called EdNet.	Behavioral (Clickstream)	Digital space	https://github.com/riiid/ednet
MUTLA: A Large-Scale Dataset for Multimodal Teaching and Learning Analytics	In this dataset, students' time-synchronized multimodal data records from the Squirrel AI Learning System (SAIL) are used to answer tasks of increasing degrees of complexity. These records include learning logs, videos, and EEG brainwaves.	Behavioral + Cognitive + Affective	Digital space + Physiological + Psychometric space	https://paperswithcode.com/dataset/mutla
SEED dataset	This data set consists of 15 Chinese movie clips representing the positive, neutral, and negative emotions selected to serve as the stimuli. The other variants of the data set include SEED GER and SEED FRA.	Affective	Digital space + Physiological	https://bcmi.sjtu.edu.cn/home/seed/.

V. INFERENCES

The following study was initiated to investigate how technology has enabled the capture of latent learning indicators, what devices will be helpful for data capture, what the current trend and what data sets are available that enable the research in learning analytics. This paper provides an overview for the researchers to understand the essentials and directions of the learning analytics research area. It was observed that there is a shift in emphasis from capturing behavioral characteristics of a learner in the formal learning settings to capturing cognitive and affective characteristics in the informal learning settings. EEG capturing devices can help to capture both cognitive and affective characteristics. Further the inferences drawn from the study are described in two dimensions.

1. From the perspective of handling the data from multiple sources and their integration.
2. From the perspective of connecting the learning theories to the constructs and measured parameters.

A. *Handling the data from multiple sources and its integration*

Several studies have shown that the direction toward using multiple data sources to capture student learning and research is toward integrating data from multiple sources towards predictive, prescriptive, and adaptive analytics.

Due to the enormous amount of data from multiple sources, many challenges are encountered concerning data pre-processing, data quality, and data alignment at one level. At another level, making the right choice of appropriate data integration methods.

Fusing information from either different data spaces or different characteristics refers to 'Multimodal data fusion'; an emerging field in this direction is 'Multimodal Learning Analytics.'

Literature categorizes the data fusion methods into three broad categories: rule-based, classification-based, and estimation-based.

On the other hand, researchers have fused the data based on the application at the feature level (early fusion), parameter level (decision level), or hybrid level.

Researchers started with the simple concatenation of data using mathematical operators followed by other techniques, including similarity-based approaches, probability-based approaches, and ensemble-based approaches, and the recent approach is the use of attention-based mechanisms. The authors identified a need for the studies that involves investigation of statistical association between the multimodal data thus helping to model the joint distribution of data.

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B. Connecting the learning theories with the measured constructs and parameters

The authors observed that several researchers have focused on only capturing one or more parameters and their integration towards describing the data, diagnosing the results, or predicting. However, the string connecting the measured parameters with the learning theories needs more substantial and further research.

VI. Conclusion

Though enough research is available for capturing the latent learning indicators, integrating the data from multiple sources, and the availability of suitable data sets, one of the bottlenecks for implementing on the various online platforms or LMS, is the use of external devices, which adds up to the cost. The behavioral characteristics can be easily captured due to the availability of ubiquitous cameras in the form of webcams and CCTVs, but to capture the cognitive and affective characteristics, there is a need for affordable devices and software for the effective utilization of the carried-out research work. The technology has enabled to capture the latent learning indicators including attention, cognitive load, cognitive stress, interest, excitement, engagement, frustration and boredom with the help of devices including emotiv EEG sensors. The drift from measuring the behavioral characteristics of the learners to cognitive and affective characteristics has enabled the research towards affordable devices that can capture the data with temporal resolution from milli seconds to hours and seamlessly get integrated with the existing learning management systems.

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