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Inclusive Learning: Employing Differentiated Instruction For Cefr Success

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Abstract

Despite its global reach, the Common European Framework of Reference (CEFR) often struggles to account for the learner diversity found in real classrooms. This paper argues that Differentiated Instruction (DI) offers a principled bridge between CEFR standards and inclusive practice, allowing educators to adapt content, process, product, and learning environment without compromising alignment to proficiency benchmarks. Drawing on the shared commitments of both frameworks — learner-centeredness, formative assessment, and pedagogical flexibility — the paper outlines concrete DI strategies across all six CEFR levels (A1–C2), including tiered tasks, choice boards, and scaffolded assessment designs. Empirical evidence suggests that well-implemented DI reduces affective barriers, sustains engagement, and accelerates proficiency development, with particular gains among learners with special educational needs, migrant backgrounds, or low prior attainment. The paper also addresses structural constraints — teacher workload, class size, and the scarcity of DI-compatible CEFR materials — and considers how these can be mitigated through policy reform, targeted professional development, and purposeful resource design. The overall case is that systematic differentiation within a CEFR curriculum is not merely accommodative but transformative, enabling authentic inclusion and measurable learning outcomes.

Key Words: Equity education, CEFR curriculum, Differentiated Instruction, Zone of Proximal Development.

1. INTRODUCTION

Language skills are the most sought after skillset in a person's life, more so the speaking skills. Professional, academic and personal life requires communication. A study by Tidwell et.al. states that women aged 25 to 64 years speak 21,845 words per day while men in the same age tend to speak 18,570 words per day. This reproves that communication skills are the most vital skills to ensure growth and prosperity of people. Even though verbal communication occupies a smaller percentage as compared to the nonverbal, the spoken word is still taken as the primary form of communication, as a form of expression of intent, as a form of confirmation and much more. Spoken words are as good as a verbal decree among people in higher positions. Lectures are conducted through the spoken word primarily.

Sadly, most Indian students are still tongue tied when it comes to speaking. Even though they have subject knowledge they are unable to speak out of fear, out of not knowing which words to use, and most importantly because they did not have adequate training in their classrooms. Poor vocabulary, poor grammar, poor pronunciation remain to be immediate causes behind a student being tongue tied but all these could be addressed if the students were trained to use English and improve their language skills according to the CEFR standards.

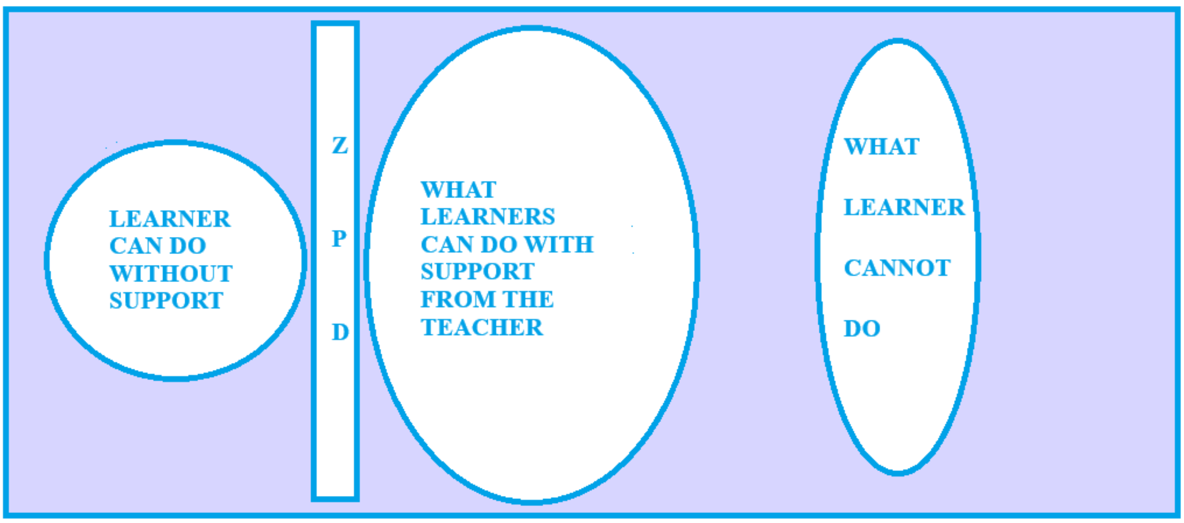
In heterogeneous class consisting of students from various socio-economical background, students' learning levels and styles will not be on the same page. Some may be visual learners while some are auditory or while some may be kinaesthetic. Some may be fast learners while some may be slow learners while some learn at average speed. Teaching a heterogeneous class a "one-formula-fits-all" method may leave the fast learner bored while the slow learner hasn't grasped anything. It may or may not benefit the average learners. To ensure learning has occurred among all the groups of students, differentiated instruction in combination with meticulously designed or chosen education technology is a feasible option.

2. DIFFERENTIATED INSTRUCTION

Differentiated instruction (D.I) help the student learn by employing their learning styles. This keeps the stress at bay. According to Tomlinson (2017) D.I is a proactive teaching philosophy that modifies content, process, product and environment based on students' readiness, interest and learning profile. By 'readiness' the students' proximity to the immediate next learning goal is determined. This concept is in alignment with Vygotsky's concept of the Zone of Proximal Development. Vygotsky's (1978) defines ZPD as 'the gap between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or in collaboration with more capable peers' (p.86).

Figure 1

Zone of Proximal Development



The word 'interest' implies students' preferred topics while 'learning profile' indicates the preferred mode of learning, driven majorly by each student's intellectual preferences. In a D.I class, scaffolding is provided based on student's inclination towards topics. For example, since most teenagers are ardent admires of movies like Harry Potter series, the Star Wars series, the Avengers series, animated movies, Japanese manga comics among others, these sources could be used as materials for scaffolding to encourage learning.

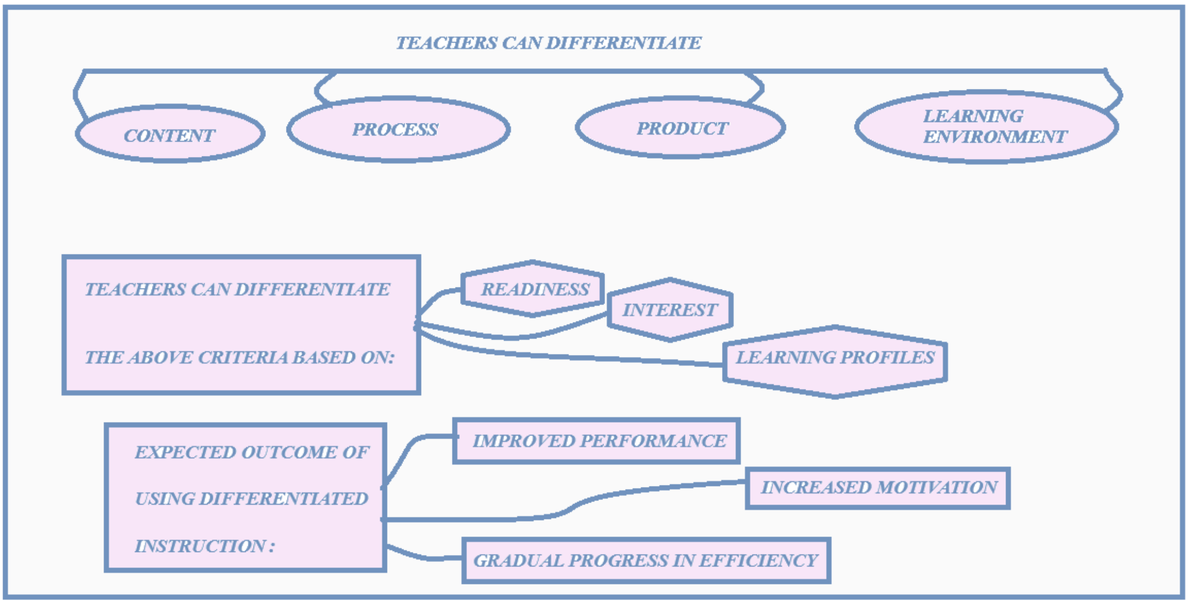
In short D.I is akin to personalizing learning by prioritizing students' preferences and therefore creating interest to learn. To design a D.I class, teachers need to identify slow learners and work together to obtain desired result by providing "multiple options for taking in information"(Tomlinson, 2001). D.I is essentially a response based implementation (CAST, 2018; Tomlinson and Imbeau, 2010) that encourages smooth learning by "removing barriers for all learners". Thus, all the learners will feel motivated to improve their skills. With the help of D.I, since 'varied modes of content engagement and expression' (Gardener, 1999) are employed, designing an instruction model that 'intentionally designs pathways for diverse learners to achieve high standards' (Stanford and Reeves, 2021) could be made possible. However, if student(s) have completed their interaction with the designed D.I content too soon or if some students have lesser than expected interaction, it means that it has to be re-designed since the 'goal is to challenge every learner but not to provide easier work for some' (Tomlinson, 2001). In fact, D.I aims to ensure all students have access to meaningful, challenging learning (Stanford and Reeves, 2021). D.I thrives on formative assessment (Tomlinson, 2014 a) and thorough needs analysis. Continuous, phased, timed assessment provides clear guidance and necessary mental impetus by promoting critical thinking and problem-solving skills (Mertens et al., 2022) and strives to reduce achievement gaps (Karaman, 2021).

3. KEY ELEMENTS OF D.I

The key elements of D.I are content, process, product and learning environment. They are the factors on which differentiation is carried out.

Figure 2

DI in a nutshell



3.1 Content

In a word, content is what students learn. Content of instruction may be novels, short stories, biographies, poetry, subject concepts and many more. The word 'content' refers to the materials and topics selected as a part of instruction. Content is what students learn. Content includes various texts, using multi-media resources or providing direct instruction to small groups (Heacox, 2012). Content depends on the “readiness” and “interest” of students. Readiness refers to a student's current knowledge, understanding, and skill level relative to a specific curriculum goal. To determine readiness, and subsequently, the content, DI teachers should evaluate the pre-assessment scores on upcoming units, or the results from end-of-unit tests from the previous unit or grade level or evaluate student performance on diagnostic tasks (e.g., solving a complex problem, writing a short response to a prompt) or through in-class performance on tasks and quizzes. Interest refers to a student's passions, hobbies, and intellectual curiosities. Teachers can determine student interests through interest surveys or simply by asking students about what they do in their free time. Tapping into interest increases motivation and engagement.

3.2 Process

Precisely, it is the how to. Process is the demonstration of students’ learning outcomes, especially due to instruction. It is the way students develop understanding and knowledge of the content by involving tiered activities, learning stations or choice boards that allow students to explore concepts through different modalities (Tomlinson, 2014). Process encompasses learning styles, intelligence preferences, and environmental factors. DI teachers are advised to look for students learning preferences – whether the students are visual, auditory, kinesthetic, or tactile learners. By conducting a Multiple Intelligences test by Howard Gardner, teachers can determine if students show strength in linguistic, logical, spatial, bodily, musical, interpersonal, intrapersonal, or naturalist intelligences.

3.3 Product

Product is the output. Students demonstrate what they learnt, mostly via assessments. Assessments can be differentiated through options like portfolios, presentations, or models, all aligned to the same learning standards (Tomlinson and Moon, 2013). Progress in learning is measured in the terms of whether or not the student has achieved the ZPD. This is measured with, mostly, formative assessment. Product heavily depends on a student's mindset, emotions, and attitudes toward learning, and themselves as a learner. Students levels of confidence and self-efficacy, responses to challenge (growth mindset vs. fixed mindset), levels of motivation and engagement must be taken into consideration.

3.4 Learning environment

Learning environment is the classroom - virtual or face to face. The teacher plays a key role in making the students welcome and heard. This includes inclusivity, variety, letting the students work independently and ensuring the classroom and teaching materials are free of bias or prejudice. A positive learning environment that empowers the learners is ensured by the teacher by creating flexible, respectful and culturally appropriate teaching materials and support (Sousa and Tomlinson, 2018). A sense of belonging is crucial to a positive learning environment.

4. HISTORY OF D.I

Early traces of D.I can be seen in 18th and 19th centuries in one room class or schools where students of different ages and knowledge levels are taught in the same room. A primary level learner to a high school level learner share the same learning environment and most likely the same instructor. To cater to all the students, these teachers have unwittingly laid foundation for D.I. Thomas S. Popekewitz (1983) explains D.I as "Individually Guided Education, a management plan for pacing children through a standardized, objective-based curriculum". Differentiation is achieved through group/peer work, peer teaching, task-based instruction and formative assessment. As time progressed, education philosophy evolved into grouping children of same age into one class, teaching one curriculum and collectively assessing them formatively and summatively.

During the 20th century, educators have taken the needs of individual students especially the slow learners into consideration. This brought back the core tenets of differentiated education into play. With the civil rights movement advocating equality, education has become inclusive, paving way for students with disability. Thus teachers had learnt to adapt instruction for diverse learners (Stanford & Reeves, 2021) following laws like IDEA (1975), thus making DI a necessity. In 1905, a psychometric test to determine the development of intelligence was designed by Alfred Binet and Theodore Simon. This greatly aided the cause of the 'Gifted Education Movement' which aimed to identify students who require heavy scaffolding (Binet & Simon, 1916). Terman (1925) demonstrated that gifted children are academically successful, thus promoting the need for specialised education provisions. Curriculums were designs so that learning "begins with experience and ends with experience" (Dewey, 1938). Programs such as ability grouping, enrichment classes and accelerated curriculum were introduced in some schools (Davis et. al., 2014). Renzulli (1978) defined giftedness as interaction among above-average ability, creativity and task commitment. Howard Gardner (1983) has proposed multiple intelligence theory, thus making D.I much more inclusive. By taking various forms of human abilities under its umbrella, adding cultural dissimilarity and economic disadvantaged students have further diversified DI. During current times, educators' attention has shifted from the mental needs to the socio-emotional needs of gifted learners (Subotnik et. al., 2011). By the end of 20th century, the shift from identifying differences to accepting and incorporating differences has become the priority. Though DI was being implemented either in full or in parts since 18th century, Tomlinson has clearly delineated, defined and popularised it in 1995 to create equity in education through her pioneering book 'How to Differentiate Instruction in Mixed- Ability Classrooms'. Tomlinson (2014) stated that modern classrooms are a tapestry of diverse learners, varying significantly in prior knowledge, cognitive abilities, learning paces, interests, cultural backgrounds, and motivational levels.

5. D.I AND A.I

In practice, implementing DI in an Indian classroom of minimum sixty students is not an ordinary feat. Teachers often are overwhelmed and exhausted because they face significant challenges in continuously assessing individual student needs, designing and managing multiple learning paths and materials, and providing timely, specific feedback to every learner within the constraints of time, class size, and resources (Smit & Humpert, 2012; Valiandes, 2015). However with the advent of AI, teachers can plan and execute their DI classes with comparative ease. AI facilitates mastery approaches by allowing students to progress only after demonstrating competence on prerequisite concepts, providing targeted remediation, and enabling multiple attempts (Guskey, 2007) since it effectively hinges on specific, timely, and actionable feedback that helps learners understand their current state and how to reach the desired goal (Hattie & Timperley, 2007) and thereby facilitate learning by continuously presenting challenges within the learner's ZPD, optimizing cognitive growth and preventing frustration or boredom (VanLehn, 2011). In this way, teacher burnout is avoided along with keeping the students motivated.

6. KEY MECHANISMS OF AI ENABLED DI

With the aid of AI, various machine learning techniques could be employed to create learning challenges for the learner. Some of the core mechanisms are mentioned below.

6.1 Student Modeling: The Foundation of Personalization

At the core of an adaptive system lies a robust student model – a computational representation of the learner's knowledge, skills, misconceptions, and potentially affective states or learning preferences (Sison & Shimura, 1998). AI systems primarily utilize:

6.1.1 Knowledge Tracing (KT)

KT models infer a student's evolving knowledge state (probability of mastery for specific skills/concepts) based on their sequence of interactions such as correct/incorrect answers, time taken, hints used. Classical approaches like Bayesian Knowledge Tracing (BKT) (Corbett & Anderson, 1994) have been augmented by deep learning models like Deep Knowledge Tracing (DKT) (Piech et al., 2015) and Dynamic Key-Value Memory Networks (DKVMN) (Zhang et al., 2017), which capture more complex knowledge structures and dependent factors.

6.1.2 Item Response Theory (IRT)

A psychometric framework that models the relationship between a student's latent ability (θ), item characteristics (difficulty, discrimination, guessing), and the probability of a correct response (Embretson & Reise, 2000). AI systems use IRT to calibrate questions and estimate student ability with high precision, enabling highly targeted question selection. Multi-dimensional IRT (MIRT) models multiple skills simultaneously (Reckase, 2009). For example, a student with low estimated θ on "grammar" would receive easier grammar questions.

6.1.3 Learning Analytics (LA)

The measurement, collection, analysis, and reporting of data about learners and their contexts, for understanding and optimizing learning and the environments in which it occurs (Siemens & Long, 2011). AI systems continuously collect vast amounts of interaction data (response times, answer choices, hesitation patterns, and navigation paths etc.) beyond simple correctness. Machine learning algorithms analyze these patterns to infer deeper understanding, identify common misconceptions (Desmarais & Baker, 2012), predict future performance, and detect potential frustration or disengagement (affective computing elements). For example, analysing patterns of wrong answers to diagnose a specific misconception (e.g., consistently confusing "affect" and "effect").

6.2. Intelligent Question Generation (Iqg)

AI leverages NLP and deep learning to generate novel methods and questions dynamically.

6.2.1 Template-Based Generation

Using predefined templates filled with variables, AI can personalize learning based on student interests or prior performance (Heilman & Smith, 2010), which is a core tenet of DI.

6.2.2 Semantic-Based Generation

Utilizing knowledge graphs or ontologies representing domain concepts and their relationships. Systems can generate learning materials, quiz questions etc testing specific relationships (e.g., "What property distinguishes [Concept A] from [Concept B]?") (Arya et al., 2021).

6.2.3 Transformative Generation

Modifying existing questions by changing values, contexts, complexity, or format like, turning a factual recall question into an application question on the same concept (Kurdi et al., 2020).

6.2.4 Generative AI (LLMs)

Large Language Models (LLMs) like GPT-4, LLaMA, or Gemini show remarkable potential for generating diverse, coherent, and contextually relevant questions from textual input, prompts, or learning objectives (Savelka et al., 2023). They can generate multiple question types (MCQ, short answer, fill-in-the-blank, explanation prompts) and tailor language complexity. For instance, an LLM could generate a reading comprehension question about a historical event, using a passage at a specific Lexile level and focusing on a cause-effect relationship relevant to the student's current learning path.

6.3. ADAPTIVE SEQUENCING AND SELECTION

Based on the student model, AI algorithms determine the most pedagogically effective next step, which not only reduces human errors but encourages efficiency from the student.

6.3.1 Difficulty Adjustment

Selecting or generating questions at an appropriate difficulty level, calibrated to the student's current estimated ability (using IRT or KT predictions), ensuring they are challenged but not overwhelmed (within ZPD).

6.3.2 Spaced Repetition

Scheduling reviews of previously learned concepts at optimal intervals to combat forgetting, based on models of memory decay like the Ebbinghaus forgetting curve (Cepeda et al., 2008). AI optimizes the timing and content of reviews.

6.3.3 Prerequisite Enforcement & Remediation Paths

It ensure students master foundational concepts before moving to more advanced ones. If a student struggles with a prerequisite skill (e.g., basic sentence formation) needed for a current topic (e.g., essay writing), the system can automatically generate or select remedial questions or learning resources targeting that specific gap (VanLehn, 2011).

6.3.4 Misconception Targeting

Identifying specific misconceptions (e.g., via pattern analysis of wrong answers or predefined misconception libraries) and generating questions explicitly designed to confront and correct that misconception (Grawemeyer et al., 2015). For example, if a student consistently makes morphological errors, the system generates questions highlighting equivalent morphological forms and models.

6.3.5 Interest-Based Selection

Incorporating student interest profiles (explicitly stated or inferred from choices/performance) to select question contexts or topics likely to increase engagement (Hidi & Renninger, 2006). For instance, if a student is interested in sports, they might receive word games framed in a sports context.

6.4. PERSONALIZED FEEDBACK GENERATION

Feedback is arguably the most critical component of formative assessment. AI moves far beyond "Correct/Incorrect" and offers a constructive feedback.

6.4.1 Specificity

Feedback directly addresses the specific error made. For a reading comprehension question, it might highlight the sentence containing the answer (Shute, 2008).

6.4.2 Elaboration

Providing explanations, hints, worked examples, or links to relevant learning resources "specific to the error or misconception detected" (Van der Kleij et al., 2015). LLMs excel at generating natural language explanations.

6.4.3 Metacognitive prompts

Encouraging students to reflect on their thinking process "Why did you choose that answer?", "What strategy could you try next?" (Bannert et al., 2015).

6.4.4 Adaptive hints

Providing graduated levels of hints based on student need and prior help-seeking behaviour (Roll et al., 2014).

6.4.5 Affective support

Generating encouraging messages or adjusting feedback tone based on inferred frustration or confidence levels (D'Mello et al., 2014). For example, instead of just marking an incorrect history date, feedback might say: "It looks like you confused the start of World War I (1914) with the start of World War II (1939). Remember that the assassination in Sarajevo triggered WWI. Here's a short timeline video link for review."

6.5. Multimodal Personalization

Advanced systems are exploring personalization across sensory modalities:

6.5.1 Visual feedback

Generating diagrams, charts, or concept maps based on student responses (Butcher, 2006).

6.5.2 Auditory feedback

Providing verbal explanations or cues to facilitate learning.

6. 5. 3 Interactive feedback

Creates dynamic simulations allowing students to explore concepts related to their mistake (de Jong, 2019).

7. BENEFITS OF INCLUDING AI IN CLASSROOMS

AI is evolving at a faster pace and substantial evidence supports the efficacy of its underlying components and related adaptive learning technologies.

7.1 Individualized Challenge & Support

Creating a psychologically safe environment where each student is consistently working within their ZPD, reducing anxiety from overwhelming tasks or boredom from lack of challenge. Personalized feedback fosters a growth mindset (Dweck, 2006).

7.2 Adaptive Learning & Personalization

AI generally shows positive effects of adaptive learning systems on student achievement compared to non-adaptive instruction, particularly for lower-achieving students (Kulik & Fletcher, 2016; Ma et al., 2014). Personalization leads to higher engagement and motivation (Walkington, 2013).

7.3 Flexibility

Empowering students with some choice (e.g., topic selection for a question set, preferred feedback format) within the structured path, increasing motivation and ownership (Ryan & Deci, 2000).

7.4 Intelligent Tutoring Systems (ITS)

ITS, which often include sophisticated AI components, have consistently demonstrated significant learning gains across various subjects (VanLehn, 2011; Steenbergen-Hu & Cooper, 2014). For example, Cognitive Tutors have shown effect sizes of 0.5 to 1.0 standard deviations in mathematics (Koedinger et al., 1997).

7.5 Personalized Feedback

Extensive research confirms the powerful impact of specific, timely feedback on learning (Hattie & Timperley, 2007; Van der Kleij et al., 2015). AI enables feedback at a scale and specificity difficult for teachers to achieve manually.

7.6 Formative Assessment

Strong evidence supports the positive impact of formative assessment practices on student achievement, particularly for low achievers (Black & Wiliam, 1998; Kingston & Nash, 2011). AI automates and intensifies formative assessment.

7.7 Mastery Learning

Studies indicate mastery learning approaches significantly improve student outcomes and reduce variation in achievement (Guskey, 2007; Kulik et al., 1990).

7.8 AI Specific Studies

Emerging studies on AI-generated questions show promise. Research indicates NLP-generated questions can be comparable in quality to human-written ones and effective for learning (Heilman, 2011; Kumar et al., 2015). Studies on adaptive quizzing systems show improved retention and performance (Lindsey et al., 2014). LLM-based question generation, while nascent, shows high potential but also highlights quality control challenges (Savelka et al., 2023).

7.9 Data-Driven Teacher Intervention

Providing teachers with rich, actionable dashboards highlighting class trends, individual struggles, misconceptions, and readiness levels. This allows teachers to make informed decisions about grouping, targeted interventions, and whole-class adjustments, optimizing the overall classroom environment (Verbert et al., 2013). For example, a dashboard flagging 3 students struggling with a specific concept allows the teacher to pull them for a small group session while others continue their learning.

The potential benefits are substantial, in terms of increased student engagement through relevant challenges and interests, deeper mastery of concepts through timely feedback and remediation, more efficient use of learning time by focusing on individual needs, reduced cognitive load for teachers through automation of routine assessment tasks, and rich data insights empowering more informed instructional decisions. Evidence from adaptive learning, ITS, and formative assessment strongly supports the efficacy of these underlying approaches. However, this transformative potential is accompanied by significant challenges and ethical imperatives. Data privacy, algorithmic bias, equitable access, the quality of AI-generated content, the evolving role of the teacher, and the risk of neglecting socio-emotional and collaborative learning demand careful attention and proactive mitigation strategies. AI must be implemented thoughtfully, ethically, and as a supportive tool within a broader pedagogical framework led by skilled educators.

8. METHODOLOGY

8.1 Statement of The Problem

This study aims to investigate if young learners could improve their language levels according to the CEFR guidelines with the help of D.I. The research question is as follows: Does implementing differentiated instruction in everyday classes improve student's CEFR language levels? The assumed null hypothesis would be that there is no improvement in the learners' language levels.

8.2 Participants

The students participating in the experiment are undergraduates pursuing engineering course from Andhra University College of Engineering for Women. The participants are informed about this research and were given a choice whether or not to participate in the research and ensured that the data collected would not be used for any other purpose other than this research. 100 students, aged 17-18, in their first year have volunteered from various branches.

8.3 Data Collection And Experiment

This study employed mixed methods- quantitative and qualitative. A CEFR level test is conducted as a pre-test. After three months of implementing D.I in the classes, the same students were tested for their CEFR levels as post-test. Individual performance of all the participants is noted and tabulated.

8.4 Results

The McNemar and Wilcoxon tests have shown significant difference in the learning outcomes. In the pre-test, the number of students who scored various CEFR scores are as follows.

Table 1

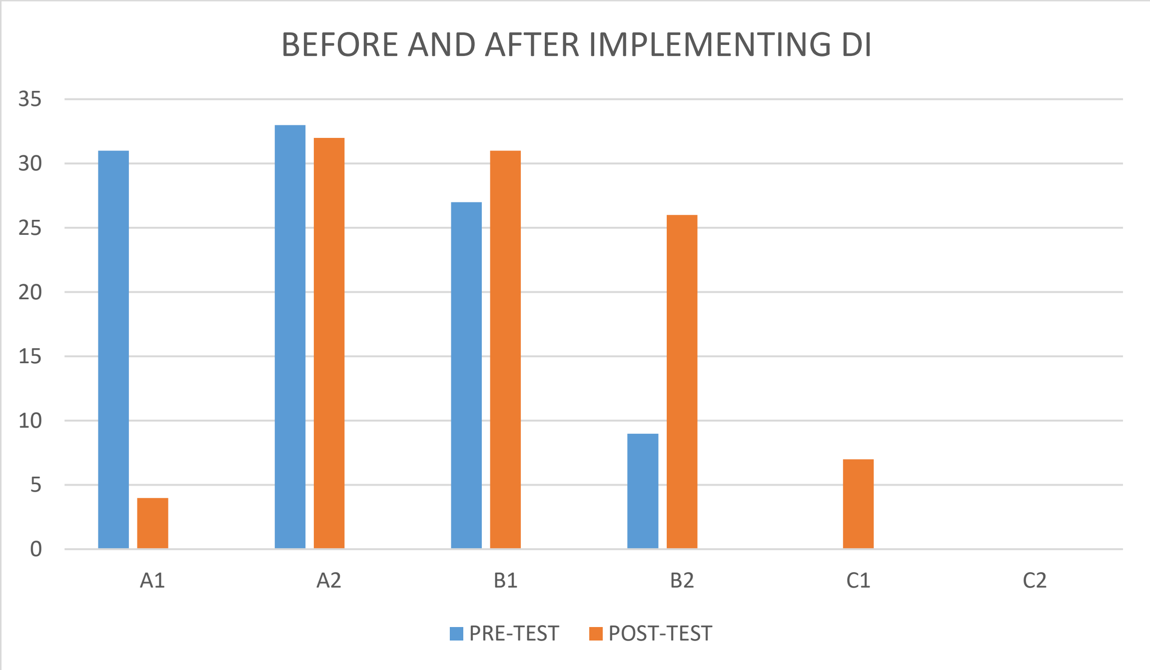
Students' scores at a glance

S. No	CEFR language level	Pre-test and total		Post-test and total	
1	A1	31	64	04	36
2	A2	33		32	
3	B1	27	36	31	57
4	B2	09		26	
5	C1	00	00	07	07
6	C2	00		00	

The pre and post test scores have shown decrease in the number of students who are in the basic level, i.e. A1 and A2, increase in the number of students in the intermediate i.e. B1 and B2 and advanced levels i.e. C1 and C2, indicating increase in the number of students who have progressed to the next level and improvement in the performance of students at an individual level. The p-value obtained in the Wilcoxon test is $1.80 * 10^{-20}$ and the test statistic (W) = 0.0 while the p-value obtained in McNemar test is $1.49 * 10^{-8}$ and McNemar's χ^2 is 0.0 showing overwhelming statistical evidence in favour of rejecting the first null hypothesis.

Figure 3

Shift in language levels pre and post intervention



8.5 Discussion

By implementing differentiated instruction as a mode of instruction, almost all students have outperformed their pre-test scores in a significant manner. While a few students have not shown any progress, none have regressed. The results obtained from both the tests show statistically significant changes. While the Wilcoxon test demonstrates statistically significant improvement in the students' CEFR levels, the McNemar test confirms transition from lower levels (A1 &A2) to higher proficiency bands, thus advocating for a skilful implementation of D.I. at graduate and other educational levels.

9. CONCLUSION

Differentiation is a slow and steady process that begins with knowing the students, understanding their needs and responding with professionalism and care. By starting small, with the help of diagnostic surveys to analyse students' readiness, with necessary scaffolding, simpler to complex activities could be assigned to the students. By regrouping the students, decided 'high' and 'low' performing groups could be avoided. By embracing the principles of D.I., each student with their unique potential could be reached out and tended to, thus unlocking potential. Thus the teacher would be the source of instruction and, more importantly, a cultivator of minds.

10. SUGGESTIONS FOR FURTHER RESEARCH

This research limits itself to developing overall language levels. Further research could consider applying DI to research on language skills individually.

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