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Transitioning Flexible Education in the Era of Generative AI Chatbot

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Abstract
The way that students and teachers learn is evolving due to the increasing adoption of generative artificial intelligence (GenAI). Effective application of these cutting-edge techniques involves self-regulated learning (SRL). GenAI chatbots, driven by sophisticated language models, deliver immediate responses and tailored feedback, which significantly impacts students learning approaches. This article presents a framework for merging SRL principles with chatbot functionalities by categorizing student interactions and utilizing process mining techniques to analyze them. These insights aim to enhance the effectiveness of chatbots in promoting SRL among learners.

Keywords: Generative Artificial Intelligence (GenAI), Self-Regulated Learning (SRL), Chatbots, Personalized Learning, Process Mining.

INTRODUCTION

Self-Regulated Learning (SRL) is a learning approach that involves active participation, modification of personal habits to achieve educational objectives, and accountability for learning outcomes[1]. SRL has been shown to positively impact academic performance, motivation, and student productivity[2]. It enhances self-efficacy, allows students to growth monitor, define skill building targets, and get response to help design a successful learning plan. Educators experience increased self-assurance and motivation as they progress toward success[3]. Learning SRL abilities can cultivate vital psychological tools and aptitudes that enable continuous learning, personal growth, and achievement in various aspects of existence[4]. Generative Artificial Intelligence (GenAI) is a cutting-edge innovation that has brought real-world learning technique to every computer and can generate original and creative media. GenAI has been utilized in various ways, such as creating question banks customized to student's comprehension and academic standards, creating personalized study plans based on individual progress, and providing tutoring or feedback through natural language processing[5]. Chatbots in education have gained profound popularity in recent times, offering personalized learning experiences through interactive and adaptive learning. They can provide instant assistance for users, access materials, revisit topics, and complete interactive practice exercises to enhance self-regulation during learning[6]. Chatbots can communicate learning goals with students, break down objectives into achievable steps, and establish realistic timelines. Recent studies connecting the SRL process to GenAI suggest a new frontier in research on this topic. The research aims to answer the following questions using recent and emerging SRL models: Which model describes the learning processes for GenAI chatbots, what ways to recognize and organize self-regulated learning processes for educational chatbots and which learning analytics activities are feasible[7]

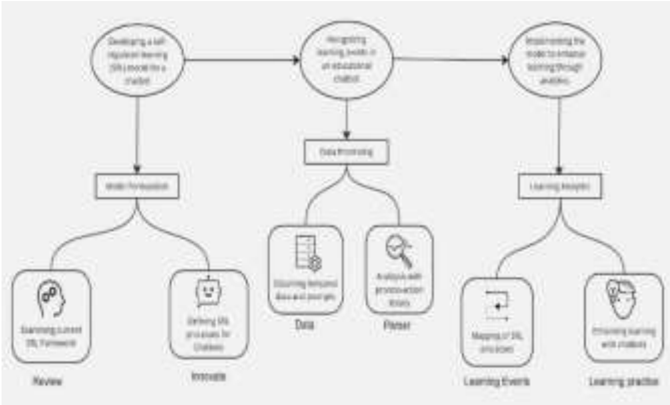

Fig 1: Learning analytics process map of building an SRL model for GenAI Chatbot framework

Self-regulated learning (SRL) refers to a student's ability to handle their education on an individual basis by creating objectives, assessing their progress, and altering strategies as required. Fundamental SRL theories encompass Zimmerman's cyclical model, Pintrich's motivational perspective, and Bandura's self-efficacy framework. To implement SRL effectively, students must develop metacognitive skills, engage in structured goal setting, and receive continuous feedback to bolster their academic performance and motivation.

2. SRL Framework for Chatbot Creation

2.1. Existing Models and Frameworks for Chatbots with SRL

Studies towards self-regulated learning commenced in 1970s. In this period, numerous frameworks, ideas, and models of self-regulated learning (SRL) have evolved and been advanced—some. More prevalent than others and some more congruent with others.

The author will not assess all available frame works but will elucidate the reasons for the selection of selected models. The endorsement of structured analysis by Panadero for a comprehensive assessment of the other all models emphasized in this part were selected for SRL analysis utilizing GenAI chatbots are connected with the illustration and development of metacognitive features Self-Regulated Learning. This provides a solid foundation for developing our framework and encourage readers and scholars to investigate alternative approaches to adherent.

Zimmerman is a renowned scholar who has developed three varying SRL frameworks with different focuses [8]. The first model, developed with the assistance of Pons, comprises 15 self-regulatory techniques including SRL behaviours [9]. This model is helpful in identifying the features of a self-regulated learner. Therefore, the seeker's questions and tracking logs presented to the chatbot can be categorized by one or more of these characteristics to offer assistance for SRL [10].

The second model, known as the Ternary Evaluation of SRL, is focused on environmental involvement, behaviour, and the person itself, drawing from Bandura's triadic model of social learning thought [11]. It suggests the precept of a cyclical mechanism in which a person's behaviour is impacted by the thought process and the context, such as social stimuli [12]. Although the triadic analysis is helpful in explaining activities in general, its relevance is not so apparent that it's not process-focused and restricted in its use structurally [13].

The final model, grounded in social-cognitive theory and known as Zimmermann's Cyclical Phases Model, explains the interrelation of metacognitive activities, cognition, and supportive strategies at the one-to-one level across three areas: forethought (task analysis and self-motivational beliefs), performance (self-regulation and self-monitoring), and self-reflection (self-assessment and self-response)[14]. Because of its comprehensiveness and broad generalizability, this model has been widely applied in SRL studies. Pintrich's work demarcates the cognitive map of SRL, developing research on the relationship between SRL and motivation. His model of SRL consists of four phases: forethought, planning, initiation, and activation; observation; regulation; and response and reflection. Each phase has domains such as cognition, motivation/affect, behaviour, and context. The phased and structured domains of SRL facilitate adjusting the model to different learning situations.

Process	**Action**	**Code**	**Description**	**Examples**
Defining	Recognition	D.R	Recognizing challenges, gaps, or areas needing attention.	"I have noticed an issue with..."; "Can you help me find the problem...?"
	Object-set	D.O	Establishing learning objectives or breaking down tasks into steps	"My goal is to understand..."; "What steps should I take to masters...?"
Seeking	Inquiry	S.I	Gathering relevant information from a chatbot or other sources	"Where can I learn more about...?"; "Give me an overview of..."
	Extract	S.E	Identifying and saving key information or insights.	"What are the essential concepts of...?"; "Summarize the main points..."
Engaging	Examine	E.EX	Revisiting prior content to verify understanding or correctness	"Does this explanation make sense...?"; "Is this interpretation accurate...?"
	Arrange	E.A	Structuring or categorizing information for better comprehension	"Can you help me format this into a table...?"; "List the key points

				clearly..."
	Practice	E.P	Practicing or reinforcing knowledge through exercises or recall.	"Create some practice questions on..."; "Test me on my understanding of..."
Reflecting	Assessment	R.A	Assessing progress and determining next steps in learning.	“What should I focus on next...?"; "How does this topic connect to...?"

Table 1: Detailed process-action model with corresponding definitions and illustrative chatbots.

Winne and Hadwin's SRL model strongly emphasize the introspective perspective. They consider self-regulated learners as actively managing their learning by employing self-monitored strategies and past methods. Their Information Processing Theory-based model consists of four recursive stages: task definition, establishing goals and planning, using study approaches, and participating in metacognitive activities to adjust strategies [15]. It also embraces five characteristics of tasks: conditions, operations, products, evaluations, and criteria—where conditions are resources and limits, operations are cognitive approaches, products are results, evaluations measure congruence, and criteria are employed for tracking [16]. This model is broadly used, particularly in virtual-assisted learning environments.

The process-action model proposed herein illustrates Winne and Hadwin's stages using Pintrich and Zimmerman's subprocesses. In the chatbot framework, SRL is divided into four processes: defining, seeking, engaging, and reflecting. Each process involves a learning action, as described in Table 1, with visual indicators to simplify actions. It should be noted that edubots are frequently applied in combination with other systems, with the learners performing individual activities with various technologies. Referring to Table 1, matching of each prompt is presented to the chatbot with a specific procedure and action.

3. Chatbots and Data Processing: Learning from Actions

This segment explains the process used for data computation in order to tackle the subsequent problem in research inquiry. The next section in our series will delve into utilization of chatbots in SRL to gain insight into their functionality approaches in process mining to clarify SRL operations in educational chatbots. The raw data of learners is collected by extracting their chat history.

Figure 1 shows that information handling involves interpreting the unprocessed data, which includes the instructions provided by the seeker via process–action repository detailed in Table 1. Each prompt is physically assigned to the process action it is performing code based on the information provided and an example prompt. In this contemplative study, the process is simplified by examining how the object is classified. A single action label is assigned to every prompt in the chatbot each option is presented to the user as an individual task. An action label indicates a single process only. If multiple prompts are associated with it, the same process has actions that are characterized by self-referential behaviour. After categorizing and labelling triggers with tasks and responsibilities through process mining, one can explore the interactions between learners and chatbots. Process mining constitutes a method that relies on data analysis to uncover and monitor potential risks, with a focus on corporate analytics. Improves operational efficiency by examining logs of events produced by information systems. SRL uses event logs as a representation of the prompt and looking for the log educational procedure. This requires synthesizing data into strategic insights from educational data developed in conjunction with the chatbot to better perspective SRL functions. After receiving the input parameters, an annotator will use the process–action repository to assign codes to each line of dialogue. Inter-Annotator Agreement (IAA) is applied in various fields, such as NLP, information recovery, and content analysis, where several annotators need to independently reach a measurable level of consensus in labelling or coding the data. [17]. When the agreement is satisfactory, the final codes are used to make necessary amendments to prepare the data for analysis [18] conducted by generating a connectivity matrix to describe the connection in instructions flow The regularity of each code following this, a Markov transforms the adjacency matrix. The node in the chain is made up of each action, with asymmetric connections from one node to another progression of the educational process.

Proof-of-concept

Two instances of a student using OpenAI's technology to prove their concept are presented (ChatGPT (GPT-3.5)). It was up to two students to choose their preferred theme make use of the edubot as a virtual instructor to learn and engage. Learners may stop when they feel they have sufficiently mastered the subject. The first-year student is not acquainted with a statistical subject. She is prepared to study for the Shapiro-Wilk test, which is addressed in a mid-level, under-graduation. The sequence of ChatGPT prompts is shown below. The ChatGPT prompt sequence is shown below.

Prompts	**Code**
I want to learn the Shapiro-wilk test. Where so I start?	D.O
Thanks! Can you give me an example of null and alternative hypothesis	S.I
Can you show me an example with data?	S.I
Any resources to help me calculate the test statistic?	S.I
How do I calculate the p-value without Python?	S,I
Where can I find a table to look up p-values?	S.I
In your example, p = 0.438. Can you show one where p < 0.05?	S.I
Can you plot the datasets to help me see the difference?	S.I
Just to check: W is from a formula, and p-value is from a table, right?	E.A
Does the Shapiro-Wilk test have one-tailed and two-tailed versions?	E.EX
What happens if I use this test for very large samples?	S.I
Can you quiz me to check my understanding?	S.I
Here are my answers: a, c, d, b, c. Did I get them right?	E.P
I got question 3 wrong. Can you explain it again?	E.P
I'm ready for practice problems! What should I do next?	E.EX
Actually, I'm curious about something else now.	R.A
Actually, I'm curious about something else now.	D.O

Table-2: Proof of concept for process action tags used by a learner involvement with ChatGPT to grasp about Shapiro-Wilk test (typographical errors are intentionally Left uncorrected)

Figure 2 depicts the learner's learning flowchart at both the execution and workflow levels. In the second scenario, an adult learner has a foundational understanding of the subject and practicing project management in preparation for the Certified associate in project management examination. Figure 3 presents the learning process map.

Table 3: Illustrates the flow.

N	D.R 0	D.O 2	S.I 9	S.E 0	E.EX 2	E.A 1	E.P 2	R.A 1	R.S 0
D.R	0	0	0	0	0	0	0	0	0
D.O	0	0	1	0	0	0	0	0	0
S.I	0	0	7	0	0	1	1	0	0
S.E	0	0	0	0	0	0	0	0	0
E.EX	0	0	1	0	0	0	0	1	0
E.A	0	0	0	0	1	0	0	0	0
E.P	0	0	0	0	1	0	1	0	0
R.A	0	1	0	0	0	0	0	0	0
R.S	0	0	0	0	0	0	0	0	0

At both the beginning and end of the skill development map for this student, Figure 2,3 shows an illustration.
Levels of action and process.

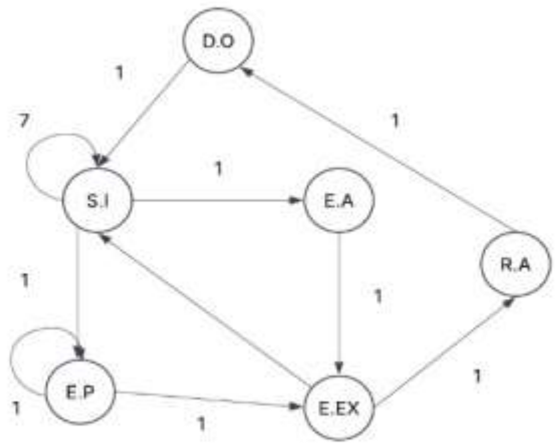

Fig 2(a): Action map

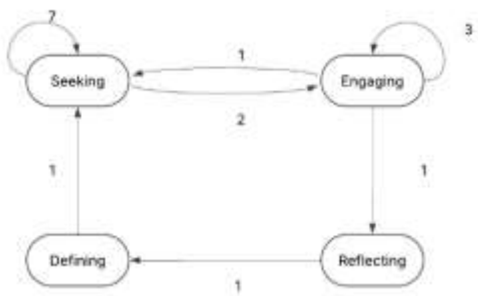

Fig 2(b): Process map

The second scenario involves an intermediate learner having knowledge of the subject. Why is this? Is pursuing project management studies in preparation for the Certified associate in project management. Examination in Project Management. The learning process map is illustrated in Figure 3.

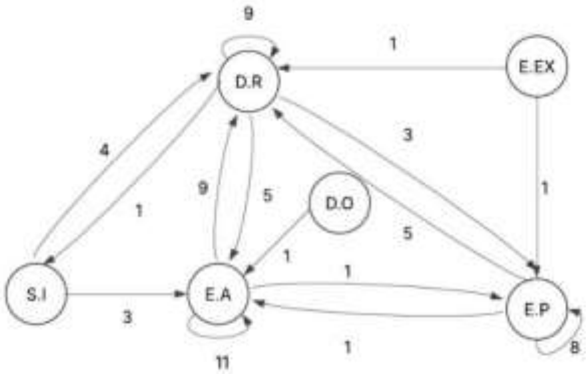

Fig 3(a): Action map

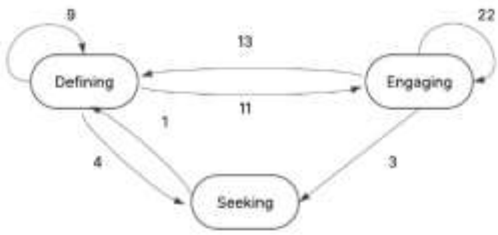

Fig 3(b):Process map

In our first case, the student acted on the chatbot with only one line of text. Seventeen prompts, most of which are about the seeking step in the SRL process in
captivating stage.
The second learner exhibits greater engagement in the subject. The defining and captivating phases of chatbot development. The provision of information is based on this preliminary data. Knowledge of how these two students learn independently in different settings.

4. Data Sources and Samples from SRL Chatbots

This work proposes a process-action map—a process mining method to determine where students tend to spend most of their time engaging with a chatbot in SRL. Having raw prompts is not enough; episodic data must be gathered and processed with edges having weights to capture temporal values. The chatbot system must be implemented to obtain such data effectively in order to classify learning actions e.g., highlighting or copying answers more accurately.
Instructors can use process-action maps to draw out student activity in the form of flowcharts, enabling

them to offer targeted suggestions. The involvement of the students in acts not originally covered by their process-action maps should be ensured.
All of this can assist in assessing how effective support structures and interventions are. Tracking how chatbots interact with them allows educators to find areas of usability bugs, content differences, or learner needs mismatches. Process mining thus informs lesson design and detects chatbot weaknesses for purposes of feedback.
Process mining decides intervention points—reminders, cues, or strategies—and acts on learning analytics linked to student performance. Researchers then build measures of performance to monitor development, assess interventions, and reveal success patterns by mapping over skill levels to maximize education resource allocation.

5. Challenges in Implementation and Performance Evaluation

Self-regulated learning (SRL) is a broad term with many frameworks stressing different views of competency development, each with special benefits. This work highlights cognitive, metacognitive, and motivating aspects; nonetheless, more study is required to include other important elements of self-regulated learning, especially with the quick acceptance of Generative AI. This covers the integration of constructivist models highlighting active learning and knowledge construction through interaction, behavioural models stressing observable actions and reinforcement learning, and collaborative learning models fostering engagement among several users or between users and a chatbot facilitating group activities. [19,20].
One example of this extension is group learning settings where chatbots help to foster shared knowledge among students. Collaborative learning-based chatbots can improve group discussions, provide comments, and help groups to solve problems together. By looking at large data sets and offering necessary insights, artificial intelligence algorithms help to create communal knowledge archives for complex topics. Using modern technologies like ChatGPT requires one to recognise their inherent boundaries and ethical conundrums. One of the main worries with generative artificial intelligence is its ability to cause hallucinations or false information creating the model aims to provide precise and relevant knowledge; yet it could unintentionally produce false or misleading materials. In learning contexts especially when students are unaware of the false information they may encounter, this can be quite negative. This weakness and implementation strategies meant to slow down the spread of false information.
Including human judgement can help to reduce the threats correlated with systematized decision-making and increase the reliability of produced content.
These studies compile remarks and views from relevant communities, stakeholders, and future end users. Understanding consumer opinions and preferences will greatly improve our approach and ensure it solves actual needs and problems. Using information from user surveys and sample implementations, a continuous and iterative validation process is supported that will progressively improves and changes the solution. This ongoing review helps us to meet evolving needs and enhance our approach for best performance.[21]
A successful methodology was created in-order to group and categorize the SRL processes associated with various stimuli employing process action labelling analysis and process mining methodologies. This classification system helps to customise and modify prompts to enhance the self-regulated learning experience and offers important new perspectives on the specific self-regulated learning tactics used by students. At the end, the possible uses of learning analytics are looked that would help to derive important

insights from the self-regulated learning processes clearly visible during interactions with educational chatbots. Process mining tools help to find important learning analytics KPIs. This information helps teachers and developers to supervise the student development, validate the efficacy of treatments, and provide customised comments, thereby improving self-regulated learning opportunities.
These results have great relevance for the blueprint of tailored learning platforms, the enhancement of seeking results, and the encouragement of learner sovereignty and competencies.

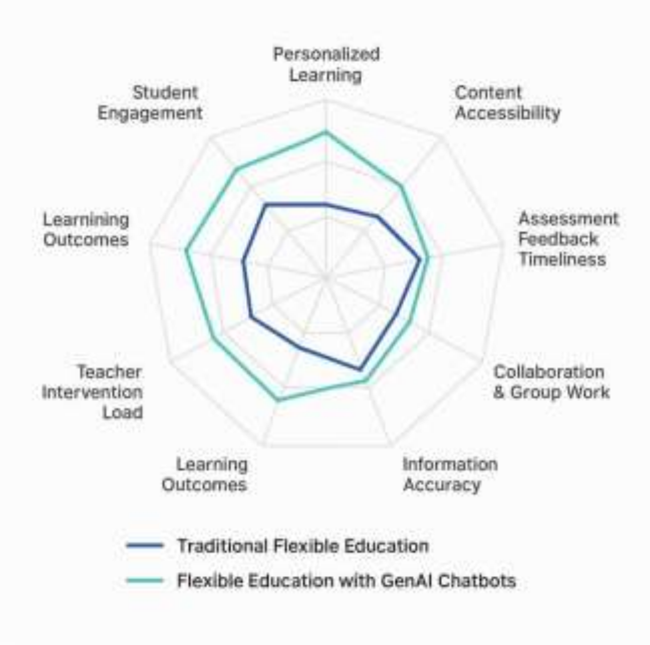

Fig 4: Radar chart visualizing performance indicators.

The radar chart contrasts flexible education with success through Generative AI (GenAI) chatbots with the traditional flexible education on eight important measures. According to facts, in all categories, GenAI chatbot-enhanced education outperforms the traditional model consistently. Student engagement, personalized learning, availability of information, and instant feedback all reflect dramatic improvements, which suggest that AI chatbots can offer more immediate, personalized, and interactive learning experiences. AI also facilitates group projects and collaboration, and improved access to resources and help lead to improved learning outcomes overall.
The graph also indicates that traditional flexible learning continues to have a narrow lead in terms of information accuracy. This may be due to the fact that GenAI at times tends to create misleading or hallucinogenic material if not checked properly.

References:

1. Zimmerman, B. J. (2008). Investigating Self-Regulation and Motivation: Historical Background, Methodological Developments, and Future Prospects. American Educational Research Journal, 45(1), 166-183. https://doi.org/10.3102/0002831207312909.
2. Dunlosky, John, and Raoul Ariel. "Self-Regulated Learning and the Allocation of Study Time." In Advances in Research and Theory, edited by Brian H. Ross, 103–140. Vol. 54. San Diego: Academic Press, 2011. https://doi.org/10.1016/B978-0-12-385527-5.00004-8.
3. Zimmerman, Barry J. "Attaining Self-Regulation: A Social Cognitive Perspective." In Handbook of Self-Regulation, 13–39. San Diego: Academic Press, 2000. https://doi.org/10.1016/B978-012109890-

2/50031-7.
4. Zimmerman, Barry J. "A Social Cognitive View of Self-Regulated Academic Learning." Journal of Educational Psychology 81, no. 3 (1989): 329–339. https://doi.org/10.1037/0022-0663.81.3.329.
5. Daniela, P. "The Relationship Between Self-Regulation, Motivation and Performance at Secondary School Students." Procedia - Social and Behavioral Sciences 191 (2015): 2549–2553. https://doi.org/10.1016/j.sbspro.2015.04.410.
6. Chung, M.K. "The Development of Self-Regulated Learning." Asia Pacific Education Review 1, no. 1 (2000): 55–66. https://doi.org/10.1007/BF03026146.
7. Wollny, Sarah, Jan Schneider, Daniel D. Mitri, Johannes Weidlich, Marc Rittberger, and Hendrik Drachsler. "Are We There Yet? A Systematic Literature Review on Chatbots in Education." Frontiers in Artificial Intelligence 4 (2021): Article 654924. https://doi.org/10.3389/frai.2021.654924.
8. Zimmerman, Barry J., and Dale H. Schunk, eds. Handbook of Self-Regulation of Learning and Performance. New York: Routledge, 2011. https://doi.org/10.4324/9780203839010.
9. Zimmerman, Barry J., and Magdaleno Campillo. "Motivating Self-Regulated Problem Solvers." In The Psychology of Problem Solving, 233–262. Cambridge: Cambridge University Press, 2003. https://doi.org/10.1017/CBO9780511615771.009.
10. Winne, Philip H., and Allyson F. Hadwin. "Studying as Self-Regulated Learning." In Metacognition in Educational Theory and Practice, 277–304. Hillsdale, NJ: Taylor & Francis, 1998.
11. Winne, Philip H. "A Cognitive and Metacognitive Analysis of Self-Regulated Learning." In Handbook of Self-Regulation of Learning and Performance, 15–32. New York: Routledge, 2011.
12. Winne, Philip H. "Inherent Details in Self-Regulated Learning." Educational Psychologist 30, no. 4 (1995): 173–187. https://doi.org/10.1207/s15326985ep3004_2.Winne, P.H. A Cognitive and Metacognitive Analysis of Self-Regulated Learning. In Handbook of Self-Regulation of Learning and Performance; Routledge: New York, NY, USA, 2011; pp. 15–32.
13. Winne, Philip H. "Self-Regulated Learning Viewed from Models of Information Processing." In Self-Regulated Learning and Academic Achievement, 153–190. New York: Lawrence Erlbaum Associates, 2001.
14. Panadero, Ernesto, Julia Klug, and Sanna Järvelä. "Third Wave of Measurement in the Self-Regulated Learning Field: When Measurement and Intervention Come Hand in Hand." Scandinavian Journal of Educational Research 60, no. 6 (2015): 723–735. https://doi.org/10.1080/00313831.2015.1066436.
15. Artstein, Ron, and Massimo Poesio. "Inter-Coder Agreement for Computational Linguistics." Computational Linguistics 34, no. 4 (2008): 555–596. https://doi.org/10.1162/coli.07-034-R2.
16. Artstein, Ron. "Inter-Annotator Agreement." In Handbook of Linguistic Annotation, 297–313. Dordrecht, Netherlands: Springer, 2017.
17. Kumar, Rangu Seshu, P. Kathiravan, V. Bhuvaneshwaran, G. S. Jagadeev, S. Krishna Prasath, and Busireddy Hemanth Kumar. "Intelligent Battery Management System Integrated with Solar PV for Residential Applications." In 2024 Second International Conference on Smart Technologies for Power and Renewable Energy (SPECon), pp. 1-6. IEEE, 2024.
18. Parimalasundar, E., R. Senthilkumar, B. Hemanth Kumar, K. Janardhan, Arvind R. Singh, Mohit Bajaj, and Viktoriia Bereznychenko. "Artificial Neural Network-Based Experimental Investigations for Sliding Mode Control of an Induction Motor in Power Steering Applications." International Journal of Intelligent Systems 2023, no. 1 (2023): 9381915.
19. Hemanth Kumar, B., Kavali Janardhan, R. Seshu Kumar, J. Ramesh Rahul, and P. Sanjeevi Kumar.

"Analysis of PWM Techniques on Multiphase Multilevel Inverter for PV Applications in Microgrids." Microgrids for Commercial Systems (2024): 133-156.

20. Suresh, K., E. Parimalasundar, B. Hemanth Kumar, Arvind R. Singh, Mohit Bajaj, and Milkias Berhanu Tuka. "Design and implementation of a universal converter for microgrid applications using approximate dynamic programming and artificial neural networks." Scientific Reports 14, no. 1 (2024): 20899.
21. Yousaf, Muhammad Zain, Arvind R. Singh, Saqib Khalid, Mohit Bajaj, B. Hemanth Kumar, and Ievgen Zaitsev. "Enhancing HVDC transmission line fault detection using disjoint bagging and bayesian optimization with artificial neural networks and scientometric insights." Scientific Reports 14, no. 1 (2024): 2361