HHAI 2024: Hybrid Human AI Systems for the Social Good
F. Lorig et al. (Eds.)

doi:10.3233/FAIA240198

Hybrid Intelligence in Academic Writing: Examining Self-Regulated Learning Patterns in an AI-Assisted Writing Task

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Abstract. The arrival of generative Artificial Intelligence (AI) in educational settings offers a unique opportunity to explore the intersection of human cognitive processes and AI, especially in complex tasks like writing. This study adopts a process-oriented approach to investigate the self-regulated learning (SRL) strategies employed by 21 doctoral and master's students during a writing task facilitated by generative AI. It aims to identify and analyze the SRL strategies that emerge within the framework of hybrid intelligence, emphasizing the collaboration between human intellect and artificial capabilities. Utilizing a learning analytics methodology, specifically lag sequential analysis (LSA), the research examines process data to reveal the patterns of learners' interactions with generative AI in writing, shedding light on how learners navigate different SRL strategies. This analysis facilitates an understanding of how learners adaptively manage their writing task with the support of AI tool. By delineating the SRL strategies in AI-assisted writing, this research provides valuable implications for the design of educational technologies and the development of pedagogical interventions aimed at fostering successful human-AI collaboration in various learning environments.

Keywords. Hybrid Intelligence, AI in education, Human-AI Interaction, Academic Writing, Higher Education, AIED

1. Introduction

The integration of Artificial Intelligence (AI) into educational contexts has marked a significant shift in the landscape of learning and instruction, particularly with the emergence of generative AI technologies. These advancements offer profound opportunities for enhancing educational experiences, especially in the development of complex cognitive skills such as writing. Writing, an essential academic skill, involves a myriad of cognitive processes, including planning, drafting, revising, and editing. The advent of generative AI in educational settings presents a novel avenue for exploring the synergy between human cognitive capabilities and artificial intelligence, especially in the realm of writing tasks. This exploration is crucial, as writing not only is a key academic skill but also serves as a window into students' cognitive processes, offering insights into how they organize, express, and refine their thoughts [1,2].

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Self-regulated learning (SRL) strategies play a pivotal role in successful writing, as they enable learners to manage their cognitive, metacognitive, and affective processes effectively [3–5]. SRL strategies are particularly relevant in tasks that require high levels of cognitive engagement and autonomy, such as writing. The integration of generative AI tools in writing tasks introduces a new dimension to SRL, as learners must navigate the interplay between their cognitive strategies and the capabilities of AI technologies. This intersection forms a hybrid intelligence system, where human cognitive processes and artificial intelligence collaborate to accomplish tasks [6,7].

Despite the potential of generative AI to transform educational practices, empirical research exploring how learners adapt their SRL strategies within AI-assisted environments, particularly in complex tasks like writing, remains limited. Understanding how learners employ SRL strategies in conjunction with generative AI tools can provide valuable insights into the nature of human-AI collaboration in different learning contexts. Moreover, examining the impact of these patterns is essential for design the effective hybrid intelligence systems for writing tasks.

This study aims to fill this gap by adopting a process-oriented approach to investigate the SRL strategies employed by doctoral and master's students during a writing task involving the use of generative AI tool(s). By focusing on the process data through learning analytics methodologies, specifically sequential clustering and lag sequential analysis (LSA), this research seeks to uncover the patterns of learners' interactions with generative AI tools. In particular, this study aims to address the following research question: What are the key patterns of actions, embedded with self-regulated learning (SRL) features, in an AI-assisted writing task?

The significance of this study lies in its potential to advance understanding of the effective integration of AI in educational practices such as academic writing. By identifying and analyzing the SRL strategies that emerge in the context of hybrid intelligence, this research contributes to the development of pedagogical interventions and the design of educational technologies that support successful human-AI collaboration. Furthermore, the findings of this study offer implications for educators and technology designers in fostering environments that leverage the strengths of both human intellect and artificial capabilities to enhance learning outcomes, particularly in the domain of academic writing.

2. Theoretical Foundations

This section outlines the theoretical framework guiding our study, focusing on three key areas: 1) SRL theory and SRL research in the context of academic writing, 2) related work on intelligent writing support systems, and 3) the adopted human-AI shared regulation (HASRL) framework for hybrid intelligence.

2.1. Self-regulated Learning Process Features in Academic Writing Tasks

The concept of self-regulated learning (SRL) has emerged as a pivotal element in the educational research landscape, signifying the capacity of learners to autonomously navigate and control their learning endeavors. At the macro-level, this self-regulatory ability encompasses a range of activities, including setting learning goals, employing strategies to achieve these goals, and monitoring progress towards them [3]. The COPES model, as articulated by Winne and Hadwin [4], presents a more detailed framework for understanding SRL through a structured analysis of its components. This model delineates SRL into five interrelated elements: Conditions, Operations, Products, Evaluations, and Standards, collectively encompassing the multifaceted nature of self-regulation in learning contexts. The significance of SRL in enhancing educational outcomes has been well-documented across various stages of learning and diverse educational contexts. The literature suggests that learners who adeptly manage their learning processes tend to achieve higher academic success and display greater persistence in the face of challenges [8,9].

Recent advancements in learning analytics and advanced technologies have further enriched our understanding of SRL by providing nuanced insights into the micro-level processes of self-regulation. These technological innovations enable the examination of learner behaviors and strategies at a granular level, thereby offering a more detailed picture of the self-regulatory processes in action [7,10]. Particularly, multimodal learning analytics have been instrumental in dissecting the complex nature of SRL, allowing researchers to explore how learners interact with various educational tasks and processes through different modalities [11,12].

In the area of academic writing, a critical skill in higher education, the exploration of SRL process features has gained momentum. Recent studies have begun to unravel how learners regulate their writing processes [13–15], employing strategies such as planning, monitoring, and revising to enhance their written outputs. For instance, Rakovic et al. [16] have demonstrated the potential of utilizing trace and process data and linguistic analysis to predict learner performance in multi-text writing tasks. This approach highlights the value of process data, including digital trace data, in uncovering the metacognitive aspects of writing, offering insights into how learners source, integrate, and synthesize information from multiple texts.

Moreover, the integration of generative AI and advanced learning analytics into the writing process presents both opportunities and challenges for SRL. The arrival of these technologies has sparked a discourse on their implications for traditional writing practices, highlighting the need for further investigation into how human-AI collaboration can be leveraged to foster hybrid intelligence in learning. Such a model aims to optimize learning outcomes by combining the strengths of human cognitive processes with the computational power of AI [7].

However, the rapid evolution of generative AI tools in educational settings has also raised concerns regarding their potential to disrupt established learning and writing processes. These concerns necessitate a deeper examination of the ways in which AI can be integrated into the learning process without undermining the essential components of SRL, such as goal setting, strategy use, and self-monitoring. As we move forward, it is essential to explore how learners should best perform learning with the technologies [17].

2.2. Intelligent Writing Support Systems

The development of intelligent writing support systems, aimed at enhancing learners' writing skills, is not a new concept, with efforts spanning over the last decade to both design these technologies and research their impact on writing processes. The evolution of these systems has been marked by significant advancements, ranging from grammar checking tools, such as Grammarly [18], to more sophisticated platforms designed to support specific aspects of the writing process. For instance, G-Asks represents a notable development, offering an intelligent automatic question generation system tailored for academic writing support [19]. This diversity in tools reflects a broad interest in leveraging technology to facilitate the complex task of writing, underscoring the potential of intelligent writing support systems to act as pivotal aids in the educational landscape.

The advent of advanced generative AI technologies has introduced a new dimension to the discourse on intelligent writing support systems, particularly concerning their application in academic writing. Generative AI's ability to produce human-like text has sparked both enthusiasm and concern regarding its implications for writing processes and outcomes. This technological leap forward raises critical questions about the integration of generative AI within intelligent writing support systems and its potential to transform writing practices in educational settings. Recent discussions have engaged various stakeholders, including teachers, learners, and educational experts, to explore perspectives on the utilization of generative AI in academic writing [20,21]. These conversations have highlighted a spectrum of views, from optimistic appraisals of AI's supportive role to cautious evaluations of its impact on learners' writing skills.

Despite the growing interest in the capabilities of generative AI and its integration into intelligent writing support systems, there remains a notable gap in empirical research, particularly concerning process-oriented investigations of writing processes with generative AI. Such research is essential for understanding not only the outcomes of using generative AI in writing tasks but also the dynamics of interaction between human learners and AI systems. A critical area of inquiry involves examining how learners can effectively collaborate with generative AI to optimize writing outputs, ensuring that the use of AI enhances rather than diminishes their writing skills. The challenge lies in identifying strategies that leverage the strengths of generative AI while fostering the development of learners' own abilities [7,22], a balance crucial for maintaining the educational value of writing tasks.

While intelligent writing support systems, including those powered by generative AI, offer promising avenues for supporting academic writing, the field stands at a crossroads. The potential of these technologies to revolutionize writing practices necessitates a deeper, process-oriented exploration of how they can be integrated into learning environments to benefit rather than hinder the development of writing skills. As the landscape of educational technology continues to evolve, further research is imperative to guide the effective and ethical use of generative AI in academic writing.

2.3. Towards Human-AI Shared Regulation for Hybrid Intelligence

The context of increasing AI adoption has led to the emergence of the concept of Hybrid Intelligence as a promising approach for integrating human and machine capabilities [6]. Hybrid Intelligence envisages a collaborative model where humans and AI systems work together, leveraging their respective strengths to achieve superior outcomes than either could accomplish alone. In the realm of education, particularly in self-regulated learning (SRL), the potential for Hybrid Intelligence through human-AI collaboration has been recognized by leading scholars [7,22]. Järvelä et al. [7] introduced the Human-AI Shared Regulation (HASRL) framework as a means to explore the self-regulatory processes within the context of human-AI collaboration, aiming to foster a synergistic relationship between human cognitive abilities and artificial intelligence.

This study adopts the COPES and HASRL framework as its theoretical foundation, focusing specifically on the traces of human SRL process features within HARSL model. While the design and development of AI systems within the HASRL framework are beyond the scope of this research, the investigation into human SRL processes in academic writing, facilitated by generative AI, provides critical insights. These insights are not only valuable in understanding the dynamics of human SRL in conjunction with AI but also hold the potential to guide the future design and development of Hybrid Intelligence systems. By examining the interplay between human SRL process features and AI in an academic writing task, this study contributes to the broader discourse on the optimal integration of AI in educational contexts, aiming to enhance learning outcomes through the strategic combination of human and machine intelligence.

3. Methods

This study employs a process-oriented learning analytics approach to investigate the process data from learners using generative AI for a writing task. This method allows for the examination of how learners dynamically interact with AI tools during the writing process, aiming to uncover insights into the SRL process features in writing with generative AI. This approach is similar to prior studies in SRL research with learning analytics [10,23,24].

3.1. Participants and Context

The participants in this study consisted of 21 graduate students, including seven PhD candidates and fourteen master's students, all enrolled in Learning and Educational Technology programs. This group was selected for their extensive experience with academic writing and the significant role that such writing plays in their academic and professional development. Insights derived from this cohort are anticipated to illuminate the dynamics of human-AI collaboration in sophisticated academic writing, which requires high standards and the articulation of complex ideas.

The data collection of this investigation was designed as an online observational study conducted via the Zoom video conferencing platform, reflecting the prevalent trends in digital communication and remote collaboration. Participants were involved in a 30-minute writing task, which required composing a short essay of approximately 500 words on the use of AI in education. This task demanded that participants express their viewpoints, supported by evidence and examples, akin to the expectations of academic writing assignments encountered in their studies.

To ensure the authenticity of the writing experience and its relevance to their academic pursuits, the design of the writing task and the evaluation rubric were closely aligned with those typically used in university settings. Participants were given a 30-minute period to complete the essay, during which they were allowed to use any resources they deemed necessary, including ChatGPT, Google Bard, Quillbot and Google Scholar. This setup aimed to replicate real-world writing scenarios, facilitating an examination of the participants' disposition to employ AI in writing tasks.

Experimental sessions were recorded to document participants' interactions with the writing task and tool usage, offering insights into their behaviors and chosen resources. A pre-survey questionnaire gathered participants' background information before each session. Identifying details were anonymized in recordings and responses to protect privacy. Informed consent was secured from all participants, ensuring the study adhered to university ethics and GDPR standards.

3.2. Qualitative Coding Analysis

Screen recordings data were analyzed and qualitatively coded to identify patterns in students' use of AI-assisted writing tools. Employing qualitative content analysis with the constant comparison method [25], each student's writing-related action was initially tagged with descriptive codes in the open coding phase. These codes were then grouped into broader categories, leading to the formulation of themes that captured the essence of the writing behaviors observed. This approach allowed for a detailed examination of the micro-processes students engaged in while writing, drawing on previous studies that explored SRL process features [23,26], specifically in academic writing tasks [15]. Table 1 shows the coding scheme for the actions recorded in this study.

Table 1. Action library used for labelling writing actions.

Action	Code	Action description
Review Instruction	INSTRUCT	Read, re-read, or review general instructions, task requirements, and the rubric.
Search Information	SEARCH	Conduct searches for words, concepts, and articles using non-generative AI tools, such as Google, Google Scholar, or other browsers.
Prompt GenAI	PROMPT	Engage generative AI platforms like ChatGPT, Google Bard, Bing Chat and prompt for information, content, feedback, references, etc.
Review GenAI Content	RE_GAI	Read, re-read or review information and content generated by generative AI.
Read Article	ARTICLE	Read, re-read or review article content.
Copy Paste Content	PASTE	Copy and paste content from non-generative AI sources (articles, notes, web pages, etc.) directly into the essay.
Copy Paste GenAI Content	PASTE_GAI	Copy and paste generated content or references from generative AI (ChatGPT, Google Bard, Bing Chat) directly into the essay.
Write Essay	WRITE	Write, edit, format, or stay in the essay zone for reviewing essay content.
Check Word Count	COUNT	Check the current word count of the essay.
Reference	REF	Manually or through applications such as Google Scholar, Mendeley, Zotero, etc., incorporate scholarly citations and references into the essay.

3.3. Sequential Clustering

To analyze the main patterns of AI-assisted writing, this study applied Agglomerative Hierarchical Clustering (AHC) using an optimal matching algorithm (OM) [27]. The analysis was conducted in Python, utilizing the scikit-learn library for its advanced machine learning functionalities. AHC, an unsupervised learning method, aims to uncover the dataset's inherent structure by grouping data points into clusters based on similarity. The optimal number of clusters was determined through the analysis of Silhouette Coefficient and a dendrogram. This approach enabled the identification of distinct writing behaviors among participants, providing valuable insights into the diverse strategies utilized in AI-assisted writing tasks.

3.4. Lag Sequential Analysis

To investigate the sequential dynamics of activities embedding SRL process features within clusters, lag sequential analysis (LSA) was utilized. This method allowed for the calculation of transitional probabilities through overlapped sampling, assessing how likely it was for certain activities to follow one another. LSA aimed to pinpoint event sequences occurring more frequently than would be expected by chance, highlighting meaningful patterns in SRL behavior. The term "lag" in LSA refers to the position of an event relative to another, with "lag 1" indicating direct sequences where events immediately follow each other, and "lag 2" highlighting indirect sequences with an intermediary action, suggesting complex or delayed learning strategies. The analysis employs a likelihood ratio chi-square (χ^2) to determine if sequence frequencies deviate significantly from expected values. When the overall χ^2 for an analysis is significant, each observed sequence can be evaluated through adjusted residuals and z-scores. Sequences with the acceptable z-scores $\geq \pm 1.96$ ($P = 0.05$) and Yule's Q value of at least 0.30 for association strength are considered significant [28]. This analysis sheds light on the structured progression of learning behaviors, providing insight into the temporal understanding of how learners navigate in AI-assisted writing.

4. Results and Findings

The outcomes of the sequential clustering analysis delineate the categorization of graduate students' behavioral patterns in AI-assisted writing tasks into two clusters. The descriptive statistical attributes of these clusters are systematically presented in Table 2.

Table 2. Descriptive statistics for two clusters detected with Agglomerative Hierarchical Clustering (AHC)

Descriptive Statistics	Cluster 1		Cluster 2	
	f	%	*f*	%
Total sequences	9	56.22	12	43.78
Average sequence length	81.89	(SD 13.45)	47.83	(SD 15.00)
Total actions	737	56.22	574	43.78
1 - Review Instruction	38	5.16	39	6.79
2 - Search information	89	12.08	63	10.98
3 - Prompt GenAI	69	9.36	62	10.80
4 - Review GenAI Content	138	18.72	77	13.41
5 - Read Article	102	13.84	74	12.89
6 - Copy Paste Content	5	0.68	10	1.74
7 - Copy Paste GenAI	54	7.33	40	6.97
8 - Write Essay	149	20.22	144	25.09
9 - Check Word Count	6	0.81	14	2.44
10- Reference	87	11.80	51	8.89

Cluster 1, characterized by a higher total number of actions in each sequence, indicates a more intensive interaction with the writing task, as evidenced by a longer average sequence length and a greater total number of actions compared to Cluster 2. Specifically, Cluster 1 shows a more frequent engagement with activities such as reviewing AI-generated content and reading articles, suggesting a deeper research and review process. Conversely, Cluster 2 exhibits shorter sequence lengths on average and a lower total action count, pointing towards a more concise and perhaps more efficient approach to the writing task. Notably, Cluster 2 participants were more likely to review instructions and check word count which may indicate task understanding and monitoring behavior, an essential SRL feature [15,29]. These differences highlight the variability in how graduate students utilize AI tools in academic writing, with some favoring extensive research and content generation, while others prioritize editing and refining their drafts.

For Cluster 1, Table 3, detailing transitional probabilities, Figure 1 illustrates the likelihood of transitioning between different activities during the AI-assisted writing process. The chi-square analysis confirms a significant association between the rows and columns within the frequency counts ($\chi 2 = 670.15$, degrees of freedom = 81, $p < .001$).

Table 3. Transitional Probabilities (Cluster 1)

Activity	INSTRUCT	PROMPT	RE_GAI	PASTE_GAI	WRITE	SEARCH	ARTICLE	REF	PASTE	COUNT
INSTRUCT	2.63	31.58	23.68	0.00	23.68	5.26	5.26	7.89	0.00	0.00
PROMPT	7.25	0.00	62.32	11.59	5.80	4.35	7.25	1.45	0.00	0.00
RE_GAI	6.52	18.12	2.17	25.36	28.99	8.70	9.42	0.72	0.00	0.00
PASTE_GAI	1.85	11.11	29.63	0.00	38.89	7.41	1.85	1.85	0.00	7.41
WRITE	8.05	8.05	29.53	6.04	1.34	5.37	16.11	22.15	2.01	1.34
SEARCH	6.74	4.49	4.49	0.00	10.11	0.00	50.56	23.60	0.00	0.00
ARTICLE	1.96	7.84	14.71	1.96	19.61	26.47	0.98	25.49	0.98	0.00
REF	1.15	1.15	1.15	0.00	45.98	36.78	12.64	0.00	1.15	0.00
PASTE	0.00	0.00	0.00	0.00	50.00	25.00	0.00	25.00	0.00	0.00
COUNT	0.00	16.67	50.00	0.00	33.33	0.00	0.00	0.00	0.00	0.00
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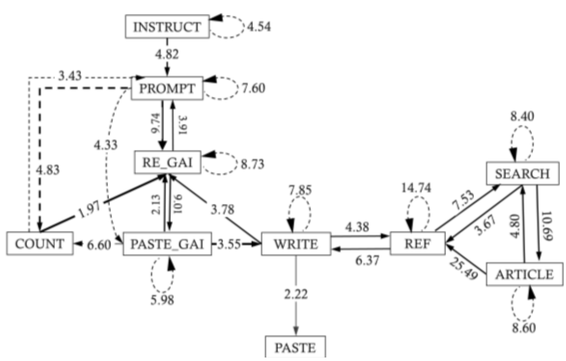

Figure 1. Cluster 1 state transition diagram of signification *lag 1* transition ($z > 1.96$, $Q < 0.30$). Edges are labeled with z-score. Lag 1 is continuous line; Lag 2 is dash line.

A notable pattern emerges from Cluster 1, indicating a high probability of moving forward and backward from "PROMPT" to "RE_GAI" (62.32%, $z = 9.74$, $Q = 0.82$), suggesting that after prompting generative AI, students are most likely to review the AI-generated content. This transition underscores the significant role of AI in shaping the initial stages of the writing process. The "WRITE" activity also shows a diverse range of subsequent activities, with the highest probabilities indicating indirect transitions back to "WRITE" (29.53%, $z_{lag2} = 7.85$, $Q_{lag2} = 0.64$) and direct transition to "REF" (22.15%, z = 4.38, Q = 0.47), suggesting iterative processes of writing and referencing. Interestingly, the transition from "PASTE_GAI" to "WRITE" (z = 3.55, Q = 0.47) is relatively high (38.89%), pointing to a significant reliance on integrating AI-generated content into the writing process. Conversely, activities like "PASTE" and "COUNT" show limited transitions, indicating these actions are less central to the workflow. These findings highlight the pivotal role of AI in facilitating the writing process, particularly in the generation and refinement of content, while also pointing to an iterative cycle of writing, referencing, and revising as key components of the students' writing strategies.

For Cluster 2, Table 4, detailing transitional probabilities, Figure 2 illustrates the likelihood of transitioning between different activities during the AI-assisted writing process. The chi-square test reveals a significant correlation between the rows and columns in the frequency data ($\chi2 = 498.15$, df = 83, $p < .001$).

Table 4. Transitional Probabilities (Cluster 2)

Activity	INSTRUCT	PROMPT	RE_GAI	WRITE	PASTE_GAI	SEARCH	ARTICLE	REF	PASTE	COUNT
INSTRUCT	10.26	38.46	12.82	23.08	2.56	5.13	2.56	2.56	2.56	0.00
PROMPT	12.90	0.00	37.10	11.29	24.19	6.45	4.84	1.61	1.61	0.00
RE_GAI	7.79	12.99	0.00	38.96	19.48	10.39	6.49	3.90	0.00	0.00
WRITE	11.89	17.48	18.18	3.50	3.50	7.69	16.78	11.89	3.50	5.59
PASTE_GAI	0.00	10.00	12.50	57.50	0.00	12.50	2.50	0.00	0.00	5.00
SEARCH	1.59	6.35	11.11	7.94	0.00	0.00	46.03	26.98	0.00	0.00
ARTICLE	0.00	1.35	9.46	36.49	4.05	28.38	0.00	16.22	4.05	0.00
REF	0.00	5.88	5.88	45.10	0.00	21.57	19.61	0.00	0.00	1.96
PASTE	0.00	0.00	10.00	40.00	0.00	10.00	10.00	0.00	0.00	30.00
COUNT	14.29	0.00	0.00	78.57	7.14	0.00	0.00	0.00	0.00	0.00
0%										100%

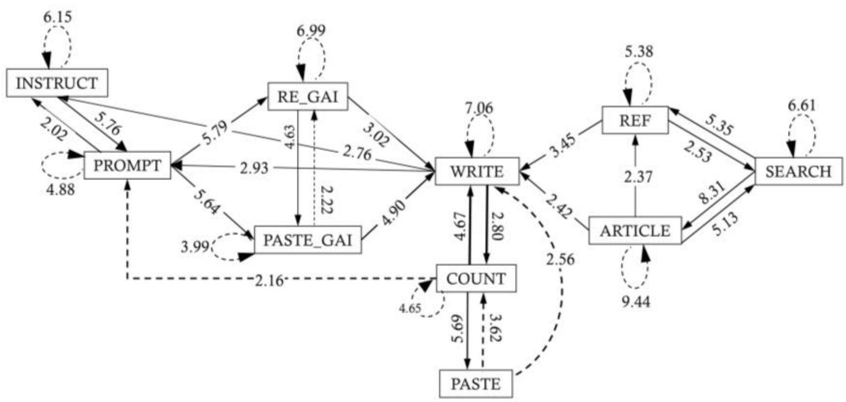

Figure 2. Cluster 2 state transition diagram of signification *lag 1* transition (z > 1.96, Q < 0.30).

In this cluster, a significant transition from "PROMPT" to "RE_GAI" (37.10%, z = 5.79, Q = 0.67) is also observed, albeit lower than in Cluster 1. However, the transition from "RE_GAI" to "WRITE" (38.96%, z = 3.02, Q = 0.36) is notably higher than in Cluster 1, suggesting a more direct path from reviewing AI content to writing. Similar to Cluster 1, the transition from "PASTE_GAI" to "WRITE" (57.50%, z = 4.90, Q = 0.64) is also high, underscoring a stronger reliance on incorporating AI-generated content directly into the writing. Nevertheless, the "WRITE" activity in Cluster 2 shows a broader distribution of subsequent activities, with a significant indirect transition back to "WRITE" (3.50%, z_{lag2} = 7.06, Q_{lag2} = 0.62) and a prominent direct transition to "COUNT" (5.59%, z = 5.69, Q = 0.61), indicating a unique focus on monitoring word count during the writing process. Furthermore, direct transition "WRITE" back to "INSTRUCT" (z = 2.67, Q = 0.45) within this cluster, unseen in cluster 1, indicates more frequent monitoring of the task requirements. This cluster also exhibits a unique pattern in the "COUNT" activity, with a substantial indirect transition to "PROMPT" (z_{lag2} = 2.16, Q_{lag2} = 0.56) and direct transition to "WRITE" (78.57%, z = 4.67, Q = 0.84). This highlights a pattern of focusing on continuous monitoring of their writing progress and the then engagement with AI-assistance can be inferred as in response to this need.

Comparing the transitional probabilities between Cluster 1 and Cluster 2 reveals nuanced differences in how each cluster engages with AI-assisted writing tools. While both clusters demonstrate a reliance on AI for generating and refining content, Cluster 2 participants show a more streamlined approach from reviewing AI-generated content to writing. This is further emphasized by their higher propensity to transition from "PASTE_GAI" directly to "WRITE" and their unique attention to word count and reviewing instruction as part of their writing process. In contrast, Cluster 1 exhibits a more iterative process involving adopting AI-generated content, referencing, and revising, with a diverse range of activities following the writing process. These differences highlight distinct strategies employed by each cluster, with Cluster 2 leaning towards a more efficient, perhaps a more goal-oriented approach, while Cluster 1 engages in a more exploratory and iterative method.

Our results align with recent studies that investigate regulatory process features at the micro-level in the context of collaborative learning [15,23,26]. For instance, Dang et al. [30] identified two predominant regulatory strategies in collaborative learning: trial-and-failure and planning-and-implementation. Moving into the domain of individual writing tasks supported by generative AI, our study adds new insights into the learning process and reveals distinct SRL behaviors within this learning activity. This contribution deepens the understanding of SRL, showing how individuals engage with and manage their writing tasks when utilizing AI tools, thereby broadening the discussion on learning processes in the context of technological advancements.

5. Discussions

This research contributes to the understanding of how graduate students utilize AI in the context of academic writing, offering a glimpse into the future of educational technology where human-AI collaboration may become a cornerstone of learning processes [7,31]. The integration of AI in educational settings, as demonstrated by this study, holds the potential to significantly augment the SRL capabilities of learners, provided that the tools are used judiciously and in ways that complement human cognitive functions. The exploration of SRL process features within the context of human-AI collaboration, particularly through the case of graduate students engaging in the academic writing task.

This study contributes to the ongoing discussions within the learning sciences regarding the collaboration between humans and AI for shared regulation in learning [7,22]. This investigation also align with the broader discourse on the role of AI in education, suggesting that while advanced AI tools, such as ChatGPT and Google Bard, offer substantial support for academic writing, the essence of human oversight and critical engagement remains irreplaceable [6,20,32,33]. The process-oriented learning analytics approach [23,30] facilitated a granular analysis of learner interactions with generative AI.

Our study shows the nuanced differences observed between the two clusters in their engagement with AI tools reflecting a broader spectrum of SRL characteristics that learners employ when interacting with technology. Specifically, the streamlined approach of Cluster 2, characterized by a direct transition from reviewing AI-generated content to writing, alongside a focused attention to word count, suggests a more efficiency-driven and goal-oriented strategy. Checking word count and task requirements aligns with the COPES model [4], showcasing students' SRL behavior [15]. This action reflects their strategic approach to meeting learning objectives by monitoring progress and adjusting efforts to align with set standards and expectations. In contrast, the iterative process observed in Cluster 1, involving extensive writing, referencing, and revising activities, indicates a preference for a more exploratory and iterative approach to learning and writing. Our findings raised a question regarding the effective integration of AI in educational practices necessitates a balanced synergy between technological affordances and human cognitive and metacognitive strategies [10,17].

The concept of Hybrid Intelligence, as evidenced through the Human-AI Shared Regulation (HASRL) framework proposed by Jarvela et al. [7], emerges as a promising paradigm for future educational technologies. This study's adherence to the HASRL framework, while focusing predominantly on the human aspects of SRL, illuminates the different SRL patterns of learners in complex cognitive tasks like academic writing with AI assistance. This study highlights the necessity of equipping learners with essential SRL skills to effectively collaborate with AI, rather than merely depending on it.

The implications of these findings are manifold. Firstly, they underscore the importance of designing AI tools that are flexible and adaptable to accommodate a wide range of learning strategies and preferences. Understanding the specific ways in which learners engage with AI to support their writing tasks can inform the development of more intuitive and supportive AI-based educational technologies. Secondly, this study highlights the potential of AI to serve as a catalyst for either enhancing or diminishing SRL. Educators can leverage these insights to guide the integration of AI tools into the curriculum, fostering environments that encourage effective SRL behaviors. Furthermore, the distinct patterns of AI tool usage identified in this study suggest the need for educational interventions that are tailored to different learning strategies. By recognizing the diversity in learner engagement with AI-assisted writing, educators and instructional designers can create more personalized learning experiences that enhance student motivation, engagement, and ultimately, learning outcomes.

6. Conclusions, Limitations, and Future Directions

In conclusion, this study not only illuminates the present state of collaboration between human intelligence and AI in academic writing but also invites further investigation into the transformative potential of AI in reshaping educational practices. By examining the nuanced ways in which students engage with AI to support their writing processes, this research contributes valuable insights into the evolving relationship between learners and AI for hybrid intelligence. It underscores the possibility of a synergistic partnership where AI tools not only assist in the mechanical aspects of writing but also stimulate critical thinking, creativity, and deeper engagement with content. Such insights are crucial for understanding the current capabilities and limitations of AI in educational settings and for envisioning future directions where AI could play a pivotal role in fostering a more interactive and engaging learning environment. This study, therefore, not only highlights the state of human-AI collaboration but also emphasizes the need for ongoing research to fully realize the potential of AI in revolutionizing educational practices, making learning more accessible, engaging, and effective for students across diverse learning environments.

This study's limitations are highlighted by its relatively small sample size, which necessitates careful interpretation of the findings. Given the focus on a specific and inherently limited group of graduate students and the adopted analytical approach with detailed qualitative coding of the micro-processes, expanding the participant pool presented a considerable challenge. Although the sample size is deemed reasonable within the confines of the targeted study population, it's important to acknowledge the impact this has on the generalizability and strength of the conclusions drawn. Consequently, the conclusions of this study should be considered preliminary, highlighting the need for further research with larger and more varied samples to corroborate and expand upon these initial findings.

Another limitation of this study is the lack of evaluation regarding the performance outcomes associated with each cluster. Future research should aim to assess the effectiveness of different writing patterns facilitated by generative AI. By doing so, it would be possible to furnish evidence supporting the significance of SRL for hybrid intelligence in educational contexts. This direction of inquiry would not only enhance our understanding of how SRL interacts with AI to influence learning outcomes but also contribute to optimizing the integration of AI tools in learning processes.

Looking ahead, the field stands at the cusp of transformative changes with the advancement of AI technologies. Future research should aim to expand the empirical base by including a broader demographic of learners, exploring diverse academic disciplines to ascertain the generalizability of the findings. Moreover, the development of hybrid human-AI systems that are sensitive to the nuances of human learning processes and capable of adapting to individual learner needs is essential. Investigating the ethical implications of AI in education, particularly in terms of data privacy, consent, and the potential for AI to influence academic integrity, will be crucial. Additionally, longitudinal studies could provide deeper insights into how the use of AI tools in academic writing evolves over time and impacts long-term learning outcomes. The exploration of Hybrid Intelligence systems that seamlessly integrate the strengths of human cognition with the computational power of AI represents a fertile area for future inquiry. Such research could significantly inform the design of next-generation educational technologies that are capable of fostering more effective, personalized, and engaging learning experiences.

Acknowledgements, Funding Statements, Declaration of Conflicting Interests

This research has been funded by the Research Council of Finland (aka. Academy of Finland) grants 350249, and the University of Oulu profiling project Profi7 Hybrid Intelligence - 352788.

The authors have no conflicts of interest regarding this study to declare.

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