SELF-REGULATED STRATEGIES AND DIFFICULTY ALLEVIATION IN AI-ASSISTED L2 ACADEMIC TASKS: A MIXED-METHODS STUDY OF ENGINEERING POSTGRADUATES IN SINO-FOREIGN COOPERATIVE EDUCATION

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I. RESEARCH DESCRIPTION

1.1 Chinese Engineering Postgraduates

Over the past two decades, the internationalisation of China's higher education has accelerated significantly. While becoming the world's largest source of outbound international students, China has also been actively introducing high-quality educational resources from abroad. As a key strategy in this internationalisation process, Sino-foreign cooperative education has grown from a few early pilot projects into a large-scale system comprising over 2,000 institutions and programmes, involving more than 600,000 enrolled students (Han, 2022). Zhejiang Province, an economically developed coastal province in eastern China, has been particularly active in this field, and Zhejiang Gongshang University (ZJSU) stands as a representative institution within this trend. A parallel development can be observed in Europe and the European Higher Education Area (EHEA), where English-Medium Instruction (EMI) has followed a similar trajectory, albeit with a later start (Dafouz, Camacho and Urquia, 2013). Examining these two pathways reveals that the scale and pace of implementation have outstripped the development of policy and research; in other words, practice has run ahead of theory. As a result, universities have been rapidly establishing English-taught programmes, yet systematic empirical research on how students cope with this challenge remains scarce (Macaro and Han, 2019). Against this backdrop, a growing number of Chinese postgraduates, particularly engineering students, are being incorporated into the EMI academic training system. Whether through joint programmes such as "2+2" and "3+1" schemes or through cooperative institutions that introduce foreign curricula and teaching materials, students are required to complete a diverse range of academic tasks in English: writing laboratory reports, literature reviews, dissertations and conference abstracts; preparing PowerPoint presentations; applying for project funding; engaging in academic email correspondence; and describing and interpreting data and figures. These activities can be collectively termed L2 academic tasks, referring to the various language production activities undertaken by learners using English as a second language in academic settings. However, existing research has predominantly focused on academic writing by humanities and social sciences students—such as essays and extended papers—while paying insufficient attention to the considerably more varied academic tasks faced by engineering students (Berdanier and Zerbe, 2018). In the context of Sino-foreign cooperative education, the situation confronting engineering students remains almost entirely unexamined. Lin and Morrison's (2021) survey of L2 engineering postgraduates and 24 engineering faculty members at three Hong Kong universities further corroborates the findings of Berdanier and Zerbe, demonstrating that the challenges L2 engineering postgraduates encounter in academic writing differ fundamentally from those of their counterparts in the humanities: they are more often required to produce descriptive and explanatory content outputs rather than construct extended argumentation. Therefore, directly applying the academic writing frameworks developed for humanities students to engineering students may lead to a mismatch between theory and reality. More importantly, for engineering students in Sino-foreign cooperative education settings, writing anxiety and cognitive difficulties are likely to become even more complex.

Among the limited studies addressing engineering postgraduates' academic writing, one empirical investigation merits particular attention. Berdanier and Zappe (2018) conducted a quantitative survey of 210 engineering postgraduates at five research universities in the United States, which for the first time revealed that this group's difficulties are concentrated in three main areas: severely insufficient writing training, with the vast majority of engineering postgraduates effectively being "self-taught"; the widespread presence of emotional barriers to writing, particularly in comparison with humanities students; and additional challenges faced by international students who are English as a Foreign Language learners. However, this study was published prior to the widespread adoption of generative AI. A natural question therefore arises: can AI tools help alleviate the difficulties outlined above? Can AI assist procrastinating students in "getting started" with writing? Can it help perfectionist students accept "imperfect first drafts"? Can it aid EFL students in

overcoming language barriers? These questions were not addressed in the aforementioned study and constitute the core point of departure for the present research.

1.2 The Roots of the Problem

This section seeks to address how the difficulties outlined in the previous section have arisen, complementing the earlier focus on what these difficulties are. Drawing on the existing literature, I identify four interrelated contributory factors: the lack of writing training, the limitations of assessment systems, insufficient supervisory guidance, and the new challenges brought by the AI era.

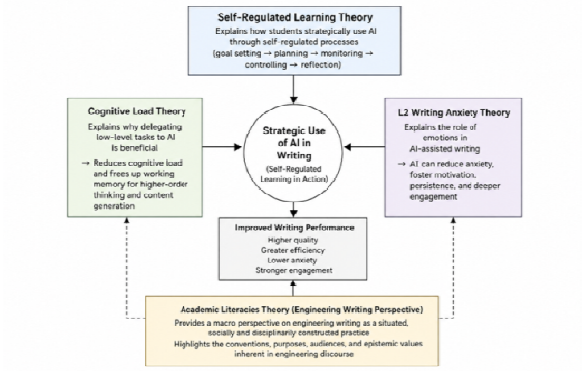
The first factor is the absence of writing training prior to postgraduate study. Gupta et al. (2022) note that many L2 students have not received systematic academic writing instruction before entering postgraduate programmes. This problem can be traced back to the language assessment mechanisms used for graduate admissions: most postgraduate programmes rely solely on IELTS or TOEFL scores as the only language requirement. However, these two standardised tests assess academic writing competence in a highly limited manner; achieving the required score does not necessarily indicate that a candidate possesses the ability to write a journal article or a dissertation, because academic writing is not an act of writing "without constraints," but rather "a dialogue conducted within rules" (AlMarwani, 2020). I therefore consider it to be, in essence, a process of cognitive and identity construction, extending far beyond a purely linguistic issue. The second factor is insufficient writing training after enrolment. In a study on English language teaching for engineering, Rus (2015) pointedly observes that writing is not engineering students' "favourite activity" or is even considered negligible, and that, given the distinctive nature of engineering training, engineering students are essentially "doers" rather than "writers." Engineering curricula also tend to treat writing as a "soft skill" rather than a core competence on a par with technical expertise. Consequently, the vast majority of engineering postgraduates are effectively "self-taught" in academic writing. Yet, the writing competence marginalised during students' academic training is precisely the core skill that will prove critical in their future professional careers (Davies, Forey and Hyatt, 2014). This contradiction constitutes another root of the difficulties engineering postgraduates face in L2 academic tasks. The third factor is the mismatch between writing competence and academic stage. Postgraduates' writing ability does not automatically improve as they progress through their academic studies. Karlen (2017) notes that there is no significant correlation between students' writing skills and the length of time they spend in higher education. A postgraduate may become increasingly proficient in a particular area of specialist knowledge, yet their academic writing ability may remain unchanged, or even regress due to a lack of practice; alternatively, they may need to reconstruct their writing framework before each task, thereby consuming additional time. This misalignment is particularly pronounced among senior doctoral students. When they are required to write journal papers or dissertations, they are suddenly confronted with a large volume of academic writing work, only to realise that they lack the necessary writing competence, which may in turn generate anxiety.

If the lack of writing training is an "explicit" problem, certain implicit cultures within engineering education constitute deeper obstacles. Existing research has found that students in the humanities or arts tend to be more inclined to seek help "outwardly," compared with engineering students, who are more inclined to look "inwardly" (Goldsmith, Willey and Boud, 2017). Engineering postgraduates seldom discuss writing tasks with their supervisors. However, simply attributing this difficulty to students' reluctance to seek help may overlook the other side of the issue: whether teachers are equally lacking in the ability or resources to provide tailored writing guidance. In an experience report on writing across disciplines, Zemliansky and Berry (2017) point out that most technical professionals, including engineering faculty, typically acquire professional writing skills "on the job," through informal learning, rather than as part of their academic and professional development. This can thus be categorised as a form of "laissez-faire writing," in which some people naturally pick it up along the way while others never do; such an experiential and accumulative mode of acquisition is far from systematic. Under these circumstances, even if students actively seek writing guidance, their supervisors may lack the ability to translate their disciplinary expertise into effective writing instruction. This finding echoes the work of Van de Poel (2012), who observed that L2 postgraduates are most concerned with basic linguistic issues such as vocabulary, grammar and tense, whereas their supervisors focus more on discourse-level matters, including text organisation, idea development and reader awareness. I would tentatively add, however, that this finding may have shifted over time, as it predates the arrival of AI; nevertheless, it must be acknowledged as a valuable reference point for comparing the pre-AI and post-AI eras. In any case, it appears that the two parties' perceptions of "what the problem is" have long been out of alignment. It is important to note that the above discussion of these difficulties draws on research findings that predate the widespread adoption of generative AI. The arrival of the AI era has not only opened up new possibilities for alleviating these difficulties but also introduced new challenges, which I will briefly address later in the

literature review when discussing scholarship since the emergence of AI up to 2026. Here, I select a few of the most salient points. On the positive side, the potential—indeed, the reality—of AI as a "helper" is beyond doubt. As noted earlier, engineering postgraduates are often reluctant to seek help from supervisors or writing centres. AI tools offer a safe and anonymous channel for assistance, enabling engineering students to obtain, without exposing their language weaknesses, all the immediate support they need and desire—translation, polishing, summarising, data description and more—often entirely free of charge (Khalifa and Albadawy, 2024; Nguyen et al., 2024). There are, of course, other AI-assisted enhancements related to academic tasks, which will be elaborated upon later. However, the use of AI also gives rise to new problems: the majority of students may become overly dependent on AI, leading to insufficient output verification and diminished critical thinking (Deep and Chen, 2025); some, though likely a minority, may forgo using AI due to distrust, thereby missing opportunities to improve efficiency. Moreover, cross-cultural conflicts regarding academic integrity, particularly within the context of Sino-foreign cooperative education, make the acceptable boundaries of AI use especially ambiguous (Ateriya et al., 2025). Chinese and foreign partner institutions may have divergent policies on AI tools, and students often lack clear guidance. This uncertainty can itself become a new source of anxiety: when using AI, students must worry not only about "whether the AI has written it correctly" but also about "whether using AI counts as cheating." In summary, the potential difficulties a considerable number of engineering postgraduates face in L2 academic tasks are rooted in a convergence of multiple contributory factors. These students are required to produce high-quality academic texts while simultaneously lacking adequate writing training and effective channels for seeking help, and they are now confronted with a regulatory vacuum concerning AI use. It should be stressed, however, that the starting point of this study is not to presuppose that engineering students inevitably have writing difficulties; rather, it seeks to investigate which students encounter difficulties, what strategies they adopt, and whether these strategies are effective.

1.3 Research Inspiration

My research is inspired by and interconnected through several theoretical frameworks; this section focuses on weaving together their relationships. I will draw on Self-Regulated Learning theory to explain how students use AI strategically, Cognitive Load theory to explain why delegating lower-order tasks is beneficial, and L2 Writing Anxiety theory to explain the role of emotional factors in AI-assisted writing. In addition, Academic Literacies theory provides a macro-level lens for understanding engineering disciplinary writing as a distinctive genre.



First, Self-Regulated Learning (SRL) theory, proposed by Zimmerman (1994), posits that when a learner successfully and effectively completes one or multiple learning episodes, this process necessarily involves an active cycle of receiving and processing information: setting goals, deploying strategies, monitoring progress, and ultimately conducting self-evaluation. The emergence of AI has rendered this process particularly salient, and lots of current research draws on this theory to conduct targeted investigations in the present era, making it a highly prominent framework (Crompton, Jones and Burke, 2022; Jin et al., 2023). I will seek to use this framework to understand how postgraduate and doctoral students utilise AI tools before, during, and after the writing process to complete their tasks, while recognising that this process may involve dynamic adjustment—that is, students may revise their writing multiple times at different stages based on AI-generated suggestions combined with their own judgement (Kim et al., 2024). However, the question of why students are willing to delegate their thinking, brainstorming, polishing, and other tasks partially—or in some cases even entirely—to AI, sometimes with favourable results, requires Cognitive Load theory (CLT)to shed light on the matter. Sweller (1988) posited that human cognitive load can be classified into three types: intrinsic load (the inherent complexity of the task itself), extraneous load (cognitive pressure unrelated to the task), and germane load (cognitive engagement that facilitates learning). In the context of L2 academic tasks, engineering postgraduates need to process both "content" (engineering knowledge) and "language" (English expression) simultaneously, which in itself constitutes a high cognitive load. If students are able to delegate lower-order tasks — such as grammar correction, lexical selection, and basic translation—to AI, they can reduce extraneous cognitive load, thereby freeing cognitive resources for higher-order thinking, such as argument construction, idea integration, and critical analysis. Thus, in my view, effective AI use may not be a form of "laziness," but rather a reallocation of cognitive resources.

Yet, a considerable number of students continue to experience writing difficulties even with AI support and assistance. Their anxiety is no longer rooted in

"being unable to write." I use the phrase "no longer" because empirical evidence from the pre-AI era allows us to identify similar patterns, whereas now this anxiety may have evolved into new forms, such as "the fear that AI use will be judged as academic misconduct" (Cheng, Calhoun and Reedy, 2025). It should be noted, however, that in the present study, L2 writing anxiety is positioned as a moderating variable rather than a core dependent variable. That is to say, this study does not presuppose that "all engineering students experience anxiety," nor does it treat "reducing anxiety" as a primary research objective; rather, anxiety is regarded as a background factor that may influence the effectiveness of AI use strategies. Students with high anxiety may be more inclined to delegate tasks in order to lighten their burden, or to verify outputs more carefully to avoid risk, whereas students with low anxiety may exhibit different strategy combinations. Finally, the core subjects of my investigation are engineering students. According to the Academic Literacies theory (ALT) proposed by Jones, Turner and Street (2000), academic writing is not a set of generic "basic skills" but is rather embedded in the discourse practices of specific disciplines. Different disciplines have distinct writing conventions, modes of argumentation, and reader expectations: the humanities value "novelty of perspective," whereas engineering places greater emphasis on "accuracy and reproducibility of information" (Lea and Street, 2006). For this reason, the L2 academic task experience of the engineering students in this study cannot simply be examined through research frameworks designed for humanities students, a realisation that also corrected an error I had made early in drafting my research proposal. The difficulties engineering students face may lie not in "how to construct complex arguments," but in "how to describe experimental data accurately,""how to explain figures and tables clearly," and "how to write laboratory reports in a standardised manner", task types that have received scant attention in research on writing in the humanities. It is precisely on this basis that the present study proposes the concept of "L2 academic tasks," expanding the scope of investigation beyond traditional "academic writing" to encompass the range of output types that engineering students actually encounter, such as laboratory reports, data descriptions, PowerPoint presentations, and academic emails. Finally, I wish to note that while Sino-foreign cooperative education programmes in China are expanding rapidly, we still know very little about the authentic learning experiences of engineering students in these settings, particularly with regard to the specific difficulties they face in L2 academic tasks and their AI use strategies. This study is precisely intended to address this research gap.

1.4 Research Questions

Building on the research background (1.1), the contributing factors (1.2), and the theoretical foundations (1.3) outlined above, this section presents my research questions. It should be noted that I am still actively reading the literature, attending academic conferences, and presenting my research proposal to different faculties and schools; therefore, these questions remain in the process of being shaped.

1.4.1 Descriptive Research Question

What self-regulated learning strategies do engineering postgraduates employ when using AI to complete L2 academic tasks? What distribution patterns do these strategies exhibit? The aim of this question is to describe the phenomenon. Existing research has established that "engineering postgraduates generally lack writing training" (Berdanier & Zappe, 2018), that "L2 postgraduates face challenges at both sentence and discourse levels" (Lin & Morrison, 2021), and that "different levels of AI literacy lead to different interaction patterns" (Kim et al., 2025). However, none of these studies have systematically measured the specific strategies−particularly across the three dimensions of planning, delegation, and verification− that engineering postgraduates use in AI-assisted L2 academic tasks. Specifically, I will address:

1. How frequently and to what extent do engineering postgraduates use AI for planning (e.g., understanding tasks, breaking down structures, developing writing plans, grasping concepts or searching for information in relevant fields, conducting literature searches)?
2. How frequently and to what extent do engineering postgraduates use AI for delegation (e.g., translation, polishing, summarising, data description)?
3. How frequently and to what extent do engineering postgraduates use AI for verification (e.g., checking output, verifying information, revising content)?
4. Are there significant differences in the use of different strategies? Do certain "typical" strategy combinations exist?

1.4.2 Relational Research Question

Is there a significant association between AI use strategies (planning, delegation, verification) and the alleviation of difficulties in L2 academic tasks? Which strategy shows the strongest association? The aim of this question is to examine relationships. If Question One answers "what is it," Question Two answers "what is the relationship." Kim et al.'s (2025) study found that students with high AI literacy performed significantly better in writing than those with low AI literacy (total score difference of 3.40 points, $p < .001$). However, that study did not pursue the further question: which specific AI use behaviour is at work− planning, delegation, or verification? Does "using it more" lead to better performance, or does "using it more wisely" make the difference? I will therefore break down AI use strategies into three dimensions and examine their respective relationships with the

alleviation of task difficulties. This may help answer the question: if we could teach students only one thing, should it be "let AI help you more,""check AI output more," or "use AI more for planning"? Specifically, I will seek to answer:

1. Is planning behaviour significantly and positively correlated with difficulty alleviation?
2. Is delegation behaviour significantly and positively correlated with difficulty alleviation?
3. Is verification behaviour significantly and positively correlated with difficulty alleviation?
4. After controlling for other variables, which strategy has the strongest predictive power?

My preliminary hypothesis is that delegation behaviour (assigning lower-order tasks to AI) may free cognitive resources and thus be positively correlated with difficulty alleviation. I also hypothesise that planning behaviour and verification behaviour (metacognitive activities) may be associated with deeper learning outcomes.

1.4.3 Moderating Effect Research Question

Does L2 writing anxiety moderate the relationship between AI use strategies and the alleviation of difficulties in L2 academic tasks? The aim of this question is to investigate boundary conditions. In other words, are the effects of AI use strategies the same for everyone, or do they vary according to students' anxiety levels? Cheng's (2004) L2 writing anxiety theory divides anxiety into three dimensions: cognitive anxiety, somatic anxiety, and avoidance behaviour. Highly anxious students may be more sensitive to language errors and more fearful of being evaluated. This emotional state may influence the effectiveness of AI use strategies. Specifically, two opposing moderating patterns may emerge: positive moderation, where highly anxious students rely more heavily on AI's "safe output," thus strengthening the effect of delegation behaviour; or negative moderation, where highly anxious students are more sceptical of AI output, thus weakening the effect of delegation behaviour. In this study, I also seek to explore whether AI serves as an "antidote to anxiety" or an "amplifier of anxiety."

These three questions can be summarised as follows: first, establish "what it is"; second, identify "what the relationships are"; and finally, determine "for whom it is more effective." Together, they form the logical chain of this study.

II. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1. Self-Regulated Learning Theory

Self-Regulated Learning (SRL) theory is one of the most influential and enduring theoretical frameworks in educational psychology. Its originator, Zimmerman, along with other scholars, continued to extend and enrich the theory well into 2012. To trace its roots, one must return to the 1980s and 1990s, when Zimmerman and Pons (1986) first advanced the core proposition of SRL theory: effective learners are not passive recipients of information, but actively engage in the cognitive, motivational, and behavioural activities of their own learning processes. In my view, this theory has not become outdated; on the contrary, it remains highly relevant in the current AI era. Whether analysed from the perspective of modern pedagogy or neuroscience, SRL constitutes a core principle−one that remains constant despite changing circumstances −though, of course, it has its limitations, which will be discussed later. This core principle has been continually supplemented and enriched over time. Carver and Scheier (2000) placed greater emphasis on learners' motivational issues during the learning process and elaborated on what these may entail. Pintrich, Marx and Boyle (1993) further categorised these as general motivation, goals, values, self-efficacy and beliefs, which can in fact be seen as an active, constructive process in which learners continually adjust their general motivation to achieve their learning goals more effectively and efficiently. How to monitor and how to adjust also became a focus of scholarly debate. Building on these concepts, multiple models centred on SRL were proposed by different scholars at different times, thereby creating opportunities to investigate a wide range of learning variables.

Since the 1980s, the field of SRL has developed a variety of theoretical models. Panadero (2017) conducted a systematic comparison of six of the most influential SRL models: Zimmerman's model (social cognitive perspective), Boekaerts' model (dual processing model), Winne and Hadwin's model (metacognitive perspective), Pintrich's model (emphasising motivation), Efklides' model (focusing on affect), and the socially shared regulation of learning model proposed by Hadwin, Järvelä and Miller (with a greater focus on collaboration). Among these six models, I have chosen to use Zimmerman's cyclical phase model as the core framework for two main reasons. First, Zimmerman's model is the most widely cited and most maturely applied model in the field, with citation counts significantly exceeding those of the other models. Second, the model's clear three-phase structure lends itself well to operationalisation: Forethought (task analysis, goal setting, strategic planning, outcome expectations); Performance (strategy execution, self-control, self-observation); and Self-Reflection (self-evaluation, attribution analysis, adaptive adjustment, self-judgement). These three phases form a cycle: the conclusions drawn in the self-reflection phase feed back into the forethought phase, influencing goal setting and strategy selection for the next round of learning. When these three phases are mapped onto the AI strategies of interest in this study, they can be

reframed as follows: in the first phase, using AI to understand task requirements, break down structures, formulate plans, search for core theoretical frameworks, grasp specific concepts, and conduct preliminary investigations; in the second phase, delegation − assigning lower-order or higher-order tasks to AI and beginning to actively check, verify and revise; and in the third phase, self-reflection on the extent of AI's assistance and adjustment of future strategies, or initiation of a new round of learning.

Zimmerman's model has long been successfully applied in the field of engineering education. However, it is perhaps necessary at this point to briefly outline the fundamental competencies required of engineering students and the current state of these students, as revealed by empirical research, since this is central to clearly delineating the population under investigation. International engineering education accreditation systems have reached a consensus on the competency requirements for graduates. ABET (Accreditation Board for Engineering and Technology) explicitly sets out seven student outcomes, covering both technical competencies (problem solving, engineering design, experimental analysis) and non-technical competencies (communication, teamwork, ethical responsibility, lifelong learning) (Forcael, Garces and Orozco, 2022). Of particular relevance to this study, communication competence is defined as "the ability to communicate complex engineering concepts effectively with diverse audiences," specifically including "reading, writing, speaking and listening" as well as "producing effective reports and design documentation." Yet, as noted earlier, a certain gap exists between the competency requirements of accreditation systems and educational practice. Yalvac et al. (2007) found that while engineering postgraduates nominally undertake writing-intensive courses, there is a lack of systematic monitoring and assessment, and fewer than half of the students surveyed rarely discussed writing tasks with their supervisors. In Kosnin's (2007) study, such students were classified as "apathetic/surface learners," as distinct from those who are strategic or knowledge-building in their approach. This finding is highly instructive, as engineering students are more likely to exhibit maladaptive learning motivation and self-regulatory behaviours when taking compulsory non-core foundational courses. This phenomenon persists even when the course content has been customised specifically for engineering disciplines. Targeted academic writing support is clearly regarded as a positive step, yet Fernandes (2012) argues that this alone is insufficient: students only become aware of the absence or importance of technical writing when faced with a specific task requirement, sometimes one tied to credits or instructor assignments. Part of the reason for the limited effectiveness and student neglect must also be attributed to ESP instructors themselves failing to achieve an appropriate integration of language acquisition and discipline-specific technical instruction (Kelley, 2006). Similar findings can be identified in related empirical research (Masoud and Al Muhtaseb, 2019). Another contributing factor can be traced back to the instructional design of undergraduate foundational courses. Waitz and Barrett (1997) cite the example of laboratory reports, noting that common teaching formats tend to simplify instructional management but are not conducive to developing students' writing, presentation, teamwork and other soft skills. In other words, students do not receive systematic training in "how to express themselves" at the foundational stage, making it naturally difficult for them to suddenly possess academic writing competence at the advanced stage. Thus, writing skills, specifically technical and academic writing, which are designated as core competencies by accreditation systems, actually occupy a marginalised position in engineering education.

Against the backdrop of the widespread adoption of generative AI, a natural question arises: can AI tools bridge this gap? In the current literature on engineering postgraduate writing, studies have already explicitly employed Zimmerman's model and validated its evaluative effectiveness. Hadwin and Oshige (2011) found that training interventions significantly improved students' self-regulatory behaviour, and that dynamic interrelationships exist among SRL variables. Moreover, many studies have referenced writing-related concepts such as "low self-efficacy,""procrastination" and "perfectionism" (Berdanier, 2020; Zerbe et al., 2019), which are also highly relevant to Zimmerman's model. More importantly, Zimmerman's model has been used in SRL research within technology-enhanced learning environments. In research on intelligent tutoring systems, Deep and Chen (2025) found that learners' SRL behaviours, such as monitoring and planning, were positively correlated with learning outcomes. However, other scholars, such as Xu et al. (2025), have found that AI tools can both promote and inhibit learners' metacognitive monitoring, depending largely on how the tools are used. Grinschgl and Neubauer (2022) similarly proposed the concept of "distributed self-regulation," suggesting that AI can assume some SRL functions. These studies indicate that Zimmerman's model is equally suitable for understanding student behaviour in AI-assisted learning contexts.

In summary, SRL empirical research in engineering education has made considerable progress. Researchers have identified the main learning types among engineering students and verified the effectiveness of SRL interventions. However, three limitations remain in these studies. First, the research settings have primarily been traditional classrooms or laboratory environments, with no involvement of

AI-assisted learning contexts. Second, the "learning tasks" examined have mainly been engineering design or programming, rather than L2 academic writing. Third, the research subjects have predominantly been high school or lower-year university students, rather than master's or doctoral students. The present study extends the existing literature along each of these three dimensions: situating SRL research within the novel context of AI-assisted L2 academic tasks, taking engineering postgraduates in Sino-foreign cooperative education settings as the research subjects, and exploring the relationships between AI use strategies (planning, delegation, verification) and the alleviation of task difficulties.

2.2 Cognitive Load Theory

If Self-Regulated Learning theory explains how students use AI strategically, Cognitive Load theory answers another key question: why is delegating certain tasks to AI an effective cognitive strategy?Sweller (1976) proposed Cognitive Load Theory, which stands as a significant milestone in the fields of cognitive science and educational psychology. The theory is built on a fundamental premise: human working memory has a limited capacity, and when the cognitive processing demanded by a learning task exceeds this capacity, learning outcomes are impaired. This challenged the then-prevalent belief that intensive drill and practice was the key to effective learning. The real obstacle to learning often lies not in the task itself, but in the fact that some tasks may exceed the limits of working memory. Traditional teaching assumed that giving students a clear goal−such as "solve for X"−and having them practise intensively would lead to mastery. Yet Sweller and Chandler (1991) found the opposite: when students were given no specific goal and were simply told to "figure out as many things as you can," they actually learned better and became more adept at transferring their knowledge to new situations.By the late 1980s, Cognitive Load Theory had taken formal shape. Sweller, Van Merrienboer and Paas (1998) classified cognitive load into three types: intrinsic load (the load imposed by the inherent complexity of the task itself, which is relatively fixed), extraneous load (load unrelated to the task, often arising from the way instruction or materials are presented−such as poor instructional design, cluttered layout, or language barriers), and germane load (cognitive engagement that promotes learning, such as organising information, constructing schemas, and engaging in deep understanding). As an English teacher, I can offer a simple illustration here. When I teach English syntactic structures, my students need to simultaneously analyse the relationship between each word in a sentence and every other word. If we regard words as elements, the degree of element interactivity in this process is very high, and consequently the intrinsic load is also high. Of course, students in my class who already have a strong foundation in English −those with an entry score of, say, IELTS Reading 6− may form an "integrated schema" in this process, experiencing something akin to "understanding at a glance." For those with a weaker foundation, or for complete beginners, the task is, unsurprisingly, mentally taxing. Intrinsic load, therefore, cannot be defined independently of the learner's level of expertise (Sweller, 1994). Extraneous load, on the other hand, is entirely created by the form of instruction. If I give my students a handout where page one presents a sentence, page two analyses its grammar, and page three provides the Chinese translation, every time they look at the sentence they must flip to page two for the analysis, then to page three for the translation, then back to page one to cross-reference. Their attention jumps back and forth among three locations, and before they even begin to comprehend, their minds are already half exhausted. A similar experience occurs with a double-sided test paper where the passage to be read spans both sides; students' error rates rise markedly. This is extraneous load. It is not the sentence itself that is difficult, but the layout of the materials that creates the problem. Cierniak, Scheiter and Gerjets (2009) found that integrating two sources of information spatially can significantly reduce this kind of load−a phenomenon known as the "split-attention effect." Related to this is the "modality effect": learning is more effective when material is presented in auditory form (spoken input, or having someone explain it to you) rather than purely in visual form (written text alone). This is why I explain concepts verbally while asking students to take notes, and why I sometimes record video instructions for assignments. Visual and auditory working memory can operate simultaneously, thereby expanding effective working memory capacity (Penney, 1989).

Germane load was introduced somewhat later. Again, using my own classroom as an example, suppose I assign two types of exercises. Group A: ten sentences, all following the same pattern−"The cat that... ran away"−with only the subject and verb changed. Students find this easy and finish quickly. Cognitive load is low, but what they learn is limited, as they have merely repeated the same pattern. Group B: ten sentences with different structures−The book that I borrowed was boring, The man whom she met is my uncle, The city where I grew up has changed. As students work through these, their minds must constantly switch gears: "Is this 'that' referring to a person or a thing?""What is going on with this 'whom'?""This 'where' is different again." The cognitive load is high, and the task is demanding. Yet after completing Group B, when students encounter a new sentence, even one with a structure they have never seen before, they can make a fairly accurate guess. This is good transfer. The "effort" required by Group B is germane load. It is not effort expended in vain; it helps construct the mental "schemas" I referred

to earlier. Accordingly, Zou et al. (2025) found that not all cognitive load is harmful; cognitive processing that promotes schema construction and automation, even if it consumes working memory resources, constitutes "beneficial" load. The core value of germane load lies in redefining cognitive load from "a burden to be eliminated" to "a resource to be optimised."An important development in Cognitive Load Theory, however, has been the discovery of the "expertise reversal effect." Kalyuga (2007) found that certain forms of instruction that are highly effective for novices gradually lose their effectiveness, and may even become counterproductive, as learners' expertise increases. This finding carries implications for AI-assisted learning: AI use strategies should be dynamically adjusted according to the learner's level of expertise. For novices, full-scale AI assistance−comparable to "worked examples"−may be highly effective; but as learners' competence grows, excessive reliance on AI may instead inhibit independent thinking and deep processing. This is precisely the cognitive mechanism underlying the risk of "metacognitive short-circuiting" (Johnson, 2022).Applying Cognitive Load Theory to the context of AI-assisted L2 academic writing, the following inferences may therefore be drawn. First, AI delegation behaviour can reduce extraneous cognitive load. In L2 academic writing, engineering students need to process both "content" (the accuracy of engineering knowledge) and "language" (the conventions of English expression) simultaneously. This dual-task demand in itself constitutes a high intrinsic load. If AI can take on lower-order tasks such as grammar correction, lexical selection, and basic translation, it can reduce extraneous cognitive load, thereby freeing cognitive resources for higher-order thinking such as argument construction, idea integration, and critical analysis. Second, AI use strategies need to be matched to the learner's level of expertise. According to the expertise reversal effect, students with low AI literacy may benefit more from "full assistance" provided by AI (akin to worked examples), while those with high AI literacy may gain more from "exploratory use." Effective AI use strategies are not fixed but should be dynamically adjusted according to the student's level of expertise. Third, if AI undertakes all cognitive tasks, students lose the opportunity to engage in schema construction, which is tantamount to depriving them of the conditions that generate germane load. Effective AI assistance, therefore, does not mean letting AI "do everything." Rather, it means reducing extraneous load while preserving or creating germane load, so that students are still able to engage in deep cognitive processing.

2.3 L2 Writing Anxiety Theory

L2 Writing Anxiety theory addresses the third question: how do emotional factors influence this process? L2 writing anxiety is an important concept in the field of second language acquisition research. Distinct from general "test anxiety" or "speaking anxiety," L2 writing anxiety refers specifically to the feelings of tension, worry, and fear that learners experience when writing in a second language. Building on earlier work, Cheng (2004) proposed a three-dimensional model of L2 writing anxiety and, through scale development and validation, established its operationalisability. The scales that predated this research had their limitations, which will be briefly noted later. Within Cheng's framework, L2 writing anxiety is classified into three dimensions: somatic anxiety (physiological reactions experienced during writing, such as sweating and accelerated heartbeat); cognitive anxiety (worries, self-doubt, and fear concerning writing−specifically, fear of writing poorly and fear of being evaluated); and avoidance behaviour (a behavioural tendency to evade writing tasks, such as procrastinating on or abandoning writing). It is worth noting, however, that while these three dimensions provide an operationalised framework for measurement, the research trajectory has long developed along separate paths, such as "general writing anxiety,""academic writing anxiety," or "foreign language classroom anxiety" (Wei, 2023). A critical intersection − "foreign language academic writing anxiety," the compound anxiety arising from academic writing in a non-native language−has long remained insufficiently integrated in research. This means that, in the pre-AI era, both our understanding of this complex phenomenon and the measurement instruments themselves were subject to inherent limitations.

A substantial body of empirical research indicates that L2 writing anxiety is negatively correlated with writing performance. Sabti et al. (2019) found that students with high anxiety scored significantly lower in writing than those with low anxiety. İnceçay and Genç's (2014) study of Turkish EFL students likewise found that writing anxiety was a significant predictor of writing achievement. Why does this occur? Because anxiety consumes working memory resources. When a learner's mind is occupied by worries such as "what if I write badly," there is insufficient capacity left to handle the actual writing tasks of "how to organise this argument" or "how to express this piece of evidence." From the perspective of Cognitive Load Theory, anxiety itself generates extraneous cognitive load: it is not required by the task, yet it depletes limited cognitive resources. However, this relationship is not a simple linear one. Evrim Önem (2012) found that moderate anxiety may have a "facilitating effect," as it may motivate students to invest greater effort. This phenomenon is referred to as the "inverted U-curve" hypothesis (Yerkes-Dodson Law): a moderate level of anxiety may enhance performance, whereas excessively high or excessively low anxiety may impede it.

This study also applies L2 Writing Anxiety theory to the context of AI-assisted L2 academic writing, but I must first establish the following positions. First, L2 writing anxiety is positioned as a moderating variable rather than a core dependent variable. This choice is based on two considerations. To begin with, the central concern of this study is "the alleviation of task difficulties," not "the reduction of anxiety." Students' primary motivation for using AI is typically to complete a specific task − such as producing a submittable paper − rather than to manage their emotions. Treating anxiety as a core dependent variable would risk deviating from this actual motivation. To use the earlier foreign language learning analogy: you use AI to polish your paper; your primary goal is to "make the paper look presentable," not to "make yourself less anxious." Though the two may be related, the goals are different. Moreover, the role of anxiety in AI-assisted writing may be double-edged. On the one hand, students with high anxiety may rely more heavily on AI, seeking to reduce the risk of making errors by depending on AI's "safe output"; on the other hand, students with high anxiety may also be more sceptical of AI−they may worry about AI making mistakes, about AI use being judged as academic misconduct, or about AI-generated writing not being good enough.

Second, anxiety in the AI era may have undergone a qualitative transformation. In the pre-AI era, the core of writing anxiety was the worry "I can't write well." In the AI era, the core of anxiety may have shifted towards an identity crisis−"does this still count as my writing?"−and self-efficacy doubts−"am I becoming increasingly dependent on AI?" Rashid, Malik and Sibgha Shafqat (2026) term this new type of anxiety "meta-anxiety," referring to anxiety about the deterioration of one's own cognitive abilities. This "meta-anxiety" was not captured in traditional L2 writing anxiety theory, yet it is precisely the most noteworthy emotional dimension in the context of AI-assisted writing. Although this study treats L2 writing anxiety as a moderating variable, the discussion section will draw on qualitative data to explore the possible manifestations of this new type of anxiety and its impact on AI use strategies. Do the effects of AI use strategies differ for students with different levels of anxiety? For instance, are students with high anxiety more inclined to use "delegation behaviour" (letting AI do more), or are they more inclined to use "verification behaviour" (checking AI more)? If it is found that highly anxious students benefit less from a given strategy, then future practical instructional interventions will need to be differentiated for this group.

When discussing the measurement of L2 writing anxiety, it is necessary to mention a methodological issue. Pre-AI measurement instruments, represented by the Foreign Language Classroom Anxiety Scale (FLCAS) developed by Horwitz et al. (1986), were extensively validated in the pre-AI era as having excellent reliability (Cronbach's α approximately 0.93) and stable cross-cultural validity (Aida, 1994; Cheng, Horwitz & Schallert, 1999). However, in the AI era, the validity of these instruments has come under question. Scholars have pointed out that the FLCAS is a product of the "pre-digital age," and that its theoretical foundations and measurement items primarily reflect language learning anxiety centred on interpersonal classroom interaction (Sun et al., 2026). It measures the anxiety students experience when being called upon to speak in a traditional classroom or when giving oral presentations−anxiety whose core is the fear of "performing poorly in front of others." By contrast, the anxiety contemporary students experience in AI-assisted writing is, in essence, a cognitive and identity crisis within a "human-AI symbiosis" digital ecosystem: is what I have written my own thinking, or was it generated by AI? Can I still call myself an "author"? Will excessive reliance on AI cause my thinking ability to deteriorate? I therefore argue that the obsolescence of the FLCAS lies not in reduced reliability but in the collapse of its validity. Nevertheless, the focus of this study is not to "develop a new scale," but to "explore how anxiety moderates the effects of AI use strategies." Accordingly, this study still adopts Cheng's (2004) Second Language Writing Anxiety Inventory (SLWAI) as the measurement instrument. This scale was specifically designed for writing contexts, and its three-dimensional structure remains theoretically relevant in AI-assisted writing situations.

2.4 Academic Literacies Theory and Disciplinary Writing Models

This section begins with Academic Literacies theory to address the fourth question raised at the outset: how exactly does writing differ across disciplines? Why can research frameworks developed for the humanities not simply be applied to engineering students? And why is the concept of "L2 academic tasks" proposed? Academic Literacies theory, introduced by Lea and Street (1998), represents an important supplement to and critique of traditional "academic writing" research paradigms. Its core proposition is this: academic writing is not a set of generic "basic skills," but rather a product embedded in the discursive practices of specific disciplines. In other words, there is no such thing as universally "good writing." What physicists consider a "good paper" and what historians consider a "good paper" may be two entirely different things−the former values data accuracy and logical rigour, while the latter prizes novelty of perspective and argumentative force. Using a single standard to assess writing across all disciplines inevitably creates problems. The Academic Literacies paradigm further suggests that writing a poor paper is not merely a matter of skills and rules; it also involves who you are, what position you stand upon, and what voice you speak with. For instance, when a non-native English

speaker writes a paper in English, their "authorial identity" is itself in a state of uncertainty: are they "pretending" to be a native speaker, or can they write in their own "voice"? This is not only a writing issue, but also an identity issue (Wingate, 2012). A key contribution of Academic Literacies theory is that it dismantles the notion of writing as a neutral skill. This perspective is particularly important for understanding the unique difficulties faced by L2 writers, who must not only learn "how to write," but also grapple with "speaking in one's own words through another's language." The limitations of Academic Literacies theory, however, also deserve attention. Over a decade after Lea and Street's (1998) research was published, the writing support systems in UK universities, for example, had not undergone substantive institutional change (Benesch, 2009). One reason for this may be that Academic Literacies researchers have not developed any concrete pedagogy for teaching writing. As Rose et al. (2008) noted, the model's impact on higher education policy has remained limited. This limitation has left space for other theoretical frameworks, particularly the "Writing in the Disciplines" (WID) model, to intervene. An analogy may help illustrate this: Academic Literacies theory is like an excellent diagnostician who can tell you precisely "where the root of the illness lies," but who does not offer you a prescription. Yet what educational practice needs is precisely that prescription. Unlike Academic Literacies, WID has a clear pedagogical direction: integrating writing instruction into disciplinary courses and assigning responsibility for writing instruction to subject lecturers (Deane and O'Neill, 2011). The core proposition of the WID model is that writing is not a "generic skill" to be taught by writing specialists alone; rather, it should be embedded in disciplinary curricula, delivered through collaboration between subject specialists and writing experts. This model has already found practical forms in Anglo-American higher education, such as collaboration between writing specialists and subject experts, peer tutoring, and formative assessment (promoting writing development through iterative feedback and revision) (Clinton, 2018; Kramer et al., 2019).

This shift holds considerable implications for the present study, because if we wish to improve engineering students' L2 academic writing ability, simply offering remedial writing courses is probably insufficient; it may be worth considering the integration of writing instruction into engineering courses themselves, so that engineering faculty are also involved in writing guidance. The reality, however, is far from ideal. Eriksson's (2018) research found that engineering teachers generally regard writing as a "communication tool" rather than "part of the disciplinary content." This cognitive positioning leads to the marginalisation of engineering writing instruction. It means that students do not receive systematic training in "how to express themselves" at the foundational stage, making it naturally difficult for them to suddenly possess academic writing competence at the advanced stage. Furthermore, as is well known, writing in different disciplines involves different conventions and requirements. What, then, is distinctive about writing in the engineering discipline? As I noted at the beginning, writing is not engineering students' "favourite activity." Given the distinctive nature of engineering training, the core characteristics of engineering students' writing include planning, clarity, and conciseness (Robinson and Blair, 1995). To illustrate, in the humanities—and I speak from experience here, as I come from a humanities and social sciences background and previously worked as a newspaper editor—I might write something like this: "Admittedly, it must be acknowledged that, during the experimental process, due to various unforeseeable factors, including but not limited to equipment calibration errors, fluctuations in ambient temperature and humidity, and subjective judgement biases on the part of the operator, a number of anomalous phenomena worthy of further investigation were observed." (You will notice the build-up, the qualifiers, the long sentences.) In contrast, the engineering writing approach might be: "The experiment succeeded. Three anomalies were observed: calibration error, humidity fluctuation, operator bias." (Direct, clear, concise.) These features stand in sharp contrast to those of humanities academic writing. Humanities academic writing encourages extensive citation and stylistic elegance, whereas engineering writing demands conciseness and informational accuracy. This means that directly applying academic writing research frameworks designed for humanities students to engineering students is likely to result in a mismatch between theory and reality. On the basis of the above analysis, I wish to propose the concept of "L2 Academic Tasks," expanding the scope of investigation beyond traditional "academic writing" to the diverse output tasks that engineering students actually face. Traditional "academic writing" research often presupposes that what students need to write is an "essay" or a "paper"—an argumentation-based genre that emphasises originality of ideas. Yet this presupposition may not hold for engineering students. The academic language tasks that engineering students actually encounter include writing laboratory reports, literature reviews, dissertations, and conference abstracts, as well as describing data and explaining figures and tables. Traditional research asks, "How do engineering students write papers?" But what engineering students actually ask is, "How do I describe this experimental data chart in English?" or "How do I respond to a reviewer's comments in English?" These questions are seldom addressed in traditional "academic writing" research, yet they are precisely the challenges that engineering students frequently face in real academic settings. This new concept, therefore, acknowledges, as I see it, that the

academic language tasks confronting engineering students are considerably more diverse and context-specific than "writing an essay."

2.6 Gaps and Positioning

Based on the above literature review, this study identifies four research gaps.First, the SRL framework has not yet been systematically applied to the context of AI-assisted L2 academic tasks. Existing SRL research has largely focused on intelligent tutoring systems or traditional learning environments, with relatively little attention paid to generative AI. Students' planning, monitoring, and evaluation behaviours when using GenAI may differ fundamentally from their SRL behaviours in traditional learning settings.Second, the operationalisation of AI use strategies has yet to be refined. That is, what specific behaviours constitute effective AI use remains to be clearly delineated.Third, the L2 academic tasks of engineering students have been neglected. Existing research has predominantly focused on the "academic writing" of humanities and social sciences students, while insufficient attention has been directed to the diverse range of tasks that engineering students actually face. Directly applying research frameworks designed for humanities students may result in a mismatch between theory and reality.Fourth, the role of emotional factors in AI-assisted writing has not been adequately examined. Specifically, whether L2 writing anxiety moderates the effects of AI use strategies has yet to be empirically tested.Accordingly, the core question this study seeks to address is: against the backdrop of Sino-foreign cooperative education, how do engineering postgraduates strategically use AI to complete L2 academic tasks? Are different use strategies associated with the alleviation of task difficulties? And how does L2 writing anxiety moderate this relationship? The next chapter will, on this basis, set out the research design and methodology of this study.

III. RESEARCH METHODOLOGY AND DESIGN

3.1 Research Philosophy and Theoretical Perspective

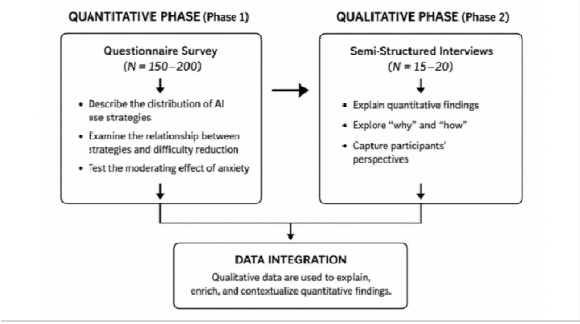
Any research design rests upon assumptions about two fundamental questions: "what is the nature of the world?" and "how can we come to know it?" This study adopts pragmatism as its core philosophical stance, while integrating interpretivism, in order to serve its central aim: understanding engineering postgraduates' strategy use in AI-assisted L2 academic tasks and its relationship with the alleviation of task difficulties.

Pragmatism, developed by philosophers such as Peirce, James, and Dewey, rests on a core proposition: the merit of a research method lies in its capacity to effectively answer the research question, not in whether it belongs to the "qualitative" or "quantitative" paradigm (Michell, 2003). Pragmatism rejects the "paradigm wars" between qualitative and quantitative research, advocating instead the flexible selection and integration of methods according to the needs of the research question. This study involves both quantitative questions (associations between strategies and difficulty alleviation, the moderating effect of anxiety) and qualitative questions (how students use AI, why certain strategies are more effective); pragmatism permits the coexistence of both. Truth is "what works" rather than "what is absolute." This study does not seek to discover universal laws, but rather to test theoretical hypotheses and describe lived experiences within a specific context−namely, Sino-foreign cooperative education and engineering postgraduates.

While pragmatism is the dominant philosophical stance, the qualitative component of this study adopts an interpretivist perspective. Interpretivism holds that social reality is constituted through actors' interpretations and meaning-making (Lin, 1998). What the researcher needs to understand is "how participants understand their own behaviour," rather than seeking context-transcendent "objective laws." The interview component aims to understand "why" students adopt a particular AI use strategy, not merely "whether" they do so. At the same time, students' AI use strategies may be moderated by contextual factors such as course requirements, supervisor attitudes, and peer influence; interpretivism allows the researcher to capture this complexity. Moreover, students' emotional responses−anxiety, trust, scepticism−when using AI are, in essence, processes of meaning construction, which require in-depth interviews to understand. Thus, my methodological position is as follows: for questions of "whether there is an association" and "how strong the association is," I will employ quantitative methods; for questions of "how it happens" and "why it works," I will employ qualitative methods. The two approaches are not opposed, but complementary.

3.2 Research Design

I plan to adopt a sequential mixed methods design, specifically a "quantitative (Phase 1) → qualitative (Phase 2)" sequence (Cameron, 2009). The rationale for this design is that the quantitative phase tests hypotheses derived from the theoretical framework (e.g., that delegation behaviour is positively correlated with difficulty alleviation), while the qualitative phase explains the mechanisms underlying the quantitative findings. Thus, the quantitative data provide "breadth" (statistical evidence of relationships between variables), while the qualitative data provide "depth" (why and how participants acted as they did).



3.2.1 Study Population and Sample

The population for this study comprises master's and doctoral engineering students enrolled in Sino-foreign cooperative programmes in China. Specifically, participants must meet the following inclusion criteria: 1) enrolled as a master's (2026 intake) or doctoral student in a Sino-foreign cooperative programme within an engineering faculty at Zhejiang Gongshang University (ZJSU); 2) Chinese native speaker, with English as a second language; 3) having completed at least one academic task in English (laboratory report, literature review, dissertation, PowerPoint presentation, academic email, etc.); 4) having experience using generative AI (such as ChatGPT, DeepSeek, etc.) to assist in completing academic tasks; and 5) voluntary participation, with signed informed consent.

I will first conduct an a priori power analysis using G*Power software (Kang, 2021). For multiple linear regression analysis (predictors including planning behaviour, delegation behaviour, verification behaviour, L2 writing anxiety, and interaction terms), setting a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and statistical power of $1-\beta = 0.80$, the estimated required sample size is N = 92. Taking into account a 20% invalid response rate, the target sample size is N = 120. To further enhance statistical power and explore subgroup differences, this study sets the target sample size at 150−200. Accordingly, I plan to adopt a combination of convenience sampling and snowball sampling, targeting engineering faculties at ZJSU for recruitment (Stratton, 2021; Goodman, 1961). Questionnaire links will be distributed through course groups and postgraduate WeChat groups recommended by Prof Zhengguo Sheng and Prof Fanzhang, and participating students will be invited to forward the link to eligible peers. Invalid responses will be screened out in the process to reach the target sample size.

Subsequently, based on the preliminary findings from the quantitative phase, I will employ maximum variation sampling and typical case sampling strategies within purposive sampling (Benoot, Hannes and Bilsen, 2016). Stratification will be designed along the following five dimensions. First, by AI use level − high-use and low-use groups − in order to compare differences in the writing experiences of students with different usage patterns. Second, by L2 writing anxiety level−high-anxiety and low-anxiety groups−to explore the moderating role of anxiety in the writing process. Third, by the degree of writing difficulty alleviation − high-alleviation and low-alleviation groups−to understand how strategy effectiveness varies across individuals. Fourth, by disciplinary field − covering different engineering disciplines − to explore possible influences of disciplinary culture on writing behaviour. Fifth, by year of study−distinguishing master's from doctoral students−to compare differences in writing needs and behaviours at different academic stages. Specifically, after completing the quantitative data analysis, I will rank and categorise participants based on their questionnaire scores, then purposefully invite students representing different types to participate in interviews. The target sample size is 15−20 participants, ensuring coverage of various combinations of the above dimensions. Analysis by Guest, Namey and Chen (2020) indicates that 12−15 interviews are usually sufficient to reach data saturation. This study sets the target at 15−20 to allow for possible attrition and in-depth exploration of specific subgroups.

3.2.2 Data Collection Methods

The quantitative phase of this study employs a questionnaire survey. The questionnaire comprises six sections with approximately 25 to 30 items, and the estimated completion time is 8 to 12 minutes. Section 1 covers informed consent and screening questions, with two items to confirm participant eligibility. Section 2 gathers information on the characteristics of the most recent L2 academic task, with four items to control for differences in task type. Section 3 measures AI use strategies, with 12 items covering the three dimensions of planning, delegation, and verification, serving as the core independent variables. Section 4 measures the degree of difficulty alleviation in L2 academic tasks, with eight items, serving as the core dependent variable. Section 5 measures L2 writing anxiety, with six items, serving as the moderating variable. Section 6 contains open-ended questions and background information, with four items to supplement qualitative data and collect demographic information.

With respect to scale sources, reliability, and validity: the planning behaviour, delegation behaviour, verification behaviour, and difficulty alleviation scales are all self-developed. The planning behaviour scale, based on Self-Regulated Learning theory, contains three items with an expected Cronbach's α greater than 0.70, measuring the extent to which learners use AI to understand tasks, break down structures, and formulate plans. The delegation behaviour scale, based on Cognitive Load Theory, contains four items with an expected α greater than 0.75, measuring behaviours such as using AI for translation, polishing,

summarising, and data description. The verification behaviour scale, based on metacognitive monitoring theory, contains five items with an expected α greater than 0.80, measuring behaviours such as checking, verifying, and revising AI output. The difficulty alleviation scale, developed on the basis of engineering task analysis, contains eight items with an expected α greater than 0.85, assessing the degree to which difficulties in language expression, structural organisation, and data description have been alleviated. The L2 writing anxiety scale, adapted from Cheng's (2004) Second Language Writing Anxiety Inventory, contains six items with an expected α greater than 0.80, covering the three dimensions of somatic anxiety, cognitive anxiety, and avoidance behaviour.

Core questionnaire items are rated on a scale from 1 to 10, where 1 represents "completely not true of me" and 10 represents "completely true of me." In the AI use strategies section, typical items include: "Before writing, I use AI to help me understand the task requirements" (planning behaviour), "I let AI help me polish grammar and expression" (delegation behaviour), and "I carefully check whether the AI-generated content is accurate" (verification behaviour). In the difficulty alleviation section, items ask about the extent to which participants have experienced relief in areas such as language expression, structural organisation, and data description—for example, "not knowing how to express my ideas in English" or "not knowing how to describe or explain data/figures"—with ratings ranging from "no alleviation at all" to "significant alleviation." In the writing anxiety section, typical items include "I am very worried that my English grammar and word choice will be wrong" (cognitive anxiety) and "I deliberately avoid using English expressions that I am not familiar with" (avoidance behaviour).

The questionnaire will be distributed via Wenjuanxing, a leading online survey platform in China, primarily through WeChat or QQ groups, supervisor recommendations, and course groups. The data collection period will last two to three weeks. To incentivise participation, students who complete the questionnaire may enter a prize draw to receive a small electronic gift card. Prior to formal distribution, two rounds of pilot testing will be conducted. The first round will be a content validity check, inviting three to five engineering postgraduates to trial the questionnaire and provide feedback on the comprehensibility and relevance of the items. The second round will be a preliminary reliability check, collecting 20 to 30 pilot responses, calculating Cronbach's α coefficients for each scale, and removing items with unacceptably low reliability accordingly. The questionnaire is provided in the Appendix.

The second, qualitative phase employs semi-structured interviews, designed to supplement and deepen the quantitative findings. The specific aims are: to explain key relationships identified in the quantitative findings (e.g., why delegation behaviour is positively correlated with the alleviation of writing difficulties); to explore deeper mechanisms that quantitative methods cannot directly capture (e.g., how students decide when to delegate and when to verify when using AI); and to capture participants' subjective experiences and meaning-making in the writing process (e.g., their genuine thoughts and feelings when using AI to write English papers). The interview guide is structured around three core themes, each containing three to five open-ended questions. The first theme focuses on AI use strategies, with core questions such as: "What academic task have you recently completed with AI? Could you describe specifically how you used it?""Do you check AI's output? How do you check it?" and "Under what circumstances would you let AI do more? When would you do it yourself?" This section is primarily based on the three-phase theory of Self-Regulated Learning. The second theme addresses writing difficulties and anxiety, with example questions such as: "What difficulties has AI helped you solve? What difficulties can it not solve?""How do you feel when using AI to write English papers (e.g., anxious, excited, confused)?" and "Do you worry about your AI use being judged as academic misconduct?" This section is underpinned by L2 Writing Anxiety theory. The third theme explores strategy adjustment, with main questions including: "Has the way you use AI changed over time? How has it changed?" and "If you were to give other students one piece of advice about how to use AI, what would you say?" This section is designed according to the self-reflection phase of Self-Regulated Learning theory.

With regard to the interview format, this study will adopt a one-on-one approach, prioritising online interviews via Tencent Meeting or WeChat video, with face-to-face interviews arranged flexibly according to circumstances. Each interview will last between 30 and 45 minutes. With participants' explicit consent, the entire interview will be audio-recorded, and the recordings will subsequently be transcribed verbatim. The interview language will be Chinese, to ensure that participants can express their views fully and naturally. The interview procedure is as follows: 24 hours before the formal interview, the interview guide will be sent to participants for their prior information, though advance preparation of responses is not required. At the beginning of the interview, the researcher will first introduce themselves and explain the study, after which an electronic informed consent form will be signed. Once consent is confirmed and recording has begun, the core question segment will proceed for approximately 30 to 40 minutes. During the interview, the researcher will flexibly follow up and seek

clarification based on participants' responses. After the recording ends, the researcher will thank the participant and issue the research incentive.

3.2.3 Data Analysis Strategies

For quantitative data, I will use SPSS 27.0 or JASP (open-source free software) for analysis. The analysis process comprises four steps. Step one is data cleaning and descriptive statistics. For missing data, listwise deletion or mean imputation will be applied to variables with less than 5% missing values, to ensure data completeness. Outliers will be detected using box plots and Z-scores, to identify possible data entry errors. Normality will be assessed using the Shapiro-Wilk test, along with skewness and kurtosis values, to inform the choice between parametric and non-parametric tests. Finally, descriptive statistics such as frequencies, means, and standard deviations will be used to profile the basic characteristics of the sample.

Step two is reliability and validity testing. Internal consistency reliability will be assessed using Cronbach's α, with an acceptance criterion of $\alpha > 0.70$. Construct validity will be examined through exploratory factor analysis, requiring factor loadings greater than 0.50.

Step three is hypothesis testing. For Sub-question One (distribution characteristics of AI use strategies), descriptive statistics (means, standard deviations, frequencies) will be employed, with descriptive tables presented. For Sub-question Two (relationships between AI use strategies and writing difficulty alleviation), Pearson correlation analysis and multiple linear regression analysis will be used, outputting correlation matrices, regression coefficients, and coefficients of determination (R^2). For Sub-question Three (the moderating effect of L2 writing anxiety), hierarchical regression analysis will be employed, with attention focused on interaction term coefficients, and simple slope plots will be generated. The regression models are specified as follows. The baseline model: difficulty alleviation = $\beta_0 + \beta_1 \times$ planning + $\beta_2 \times$ delegation + $\beta_3 \times$ verification + ε. The extended model adds control variables to the baseline model: difficulty alleviation = $\beta_0 + \beta_1 \times$ planning + $\beta_2 \times$ delegation + $\beta_3 \times$ verification + $\beta_4 \times$ anxiety + $\beta_5 \times$ year of study + $\beta_6 \times$ discipline + ε. The moderation model further incorporates interaction terms: difficulty alleviation = $\beta_0 + \beta_1 \times$ planning + $\beta_2 \times$ delegation + $\beta_3 \times$ verification + $\beta_4 \times$ anxiety + $\beta_5 \times$ (delegation $\times$ anxiety) + $\beta_6 \times$ (verification $\times$ anxiety) + ε.

Step four is supplementary analysis. Independent samples t-tests will be used to compare differences in strategy use between master's and doctoral students, and between high-anxiety and low-anxiety groups. One-way ANOVA will be employed to compare differences in strategy effectiveness across different task types (laboratory report, literature review, dissertation).

For qualitative data, I will adopt Braun and Clarke's (2006) thematic analysis approach for coding and analysis, comprising six steps. Step one is familiarisation with the data, through repeated reading of interview transcripts and making initial notes, to develop an overall sense of the data. Step two is initial coding, involving line-by-line coding of the transcripts, marking meaningful segments of discourse, and generating a coding list (e.g., "delegating translation,""verifying citations,""fear of misuse"). Step three is searching for themes, grouping related codes into preliminary themes, and producing a list of candidate themes (e.g., "benefits of delegation,""timing of verification,""sources of anxiety"). Step four is reviewing themes, examining the internal coherence of each theme and the distinctiveness between themes, yielding a revised thematic structure. Step five is defining themes, writing clear definitions and descriptions for each theme, and producing a theme definition table. Step six is report writing, presenting the final themes in the results section of the thesis, accompanied by representative quotations.

Coding examples are as follows. For the original quotation "I first let ChatGPT translate a paragraph of Chinese literature, then I revised the expression myself," the initial codes are "delegating translation + revision," grouped under the sub-theme "AI as a translation tool," and ultimately belonging to the theme "delegation behaviour." For the quotation "Every time I have to check whether the references it gives actually exist—I've been caught out before," the codes are "verifying citations" and "prior negative experience," grouped under the sub-theme "trust and verification," belonging to the theme "verification behaviour." For the quotation "Sometimes after writing I feel like it's not my own work, and it makes me a bit panicky," the codes are "authorial identity anxiety," grouped under the sub-theme "identity crisis," belonging to the theme "new types of anxiety in the AI era." In terms of analytical tools, this study will use NVivo 14 or MAXQDA (depending on available resources) to assist with coding and theme management.

It should be noted that this study adopts two strategies—juxtaposition and data transformation—to integrate the quantitative and qualitative findings (Creswell, 2009). The first is juxtaposition, whereby quantitative and qualitative findings are reported separately and then integrated in the discussion section. For example, quantitative analysis may reveal that delegation behaviour is positively correlated with the alleviation of writing difficulties; in interviews, students may also mention that "after letting AI help me with translation, I could devote more energy to argumentation." The

qualitative data thus provide a processual explanation for the quantitative finding, illustrating "why" delegation behaviour is effective in alleviating writing difficulties. The second is data transformation, whereby qualitative codes are quantified into frequency data and cross-analysed with the quantitative data. For instance, the number of interviewees mentioning "verifying AI output" can be counted and correlated or compared with their verification behaviour scores measured in the questionnaire.

With regard to the quantitative component, this study safeguards research quality along four dimensions: internal validity, external validity, reliability, and objectivity. Internal validity refers to the credibility of causal relationships between variables. As this is a correlational study and does not claim causality, strict internal validity is not pursued; nonetheless, control variables such as year of study and discipline are included in regression analyses to reduce potential confounding. External validity refers to the generalisability of findings. The sample for this study is drawn from Zhejiang Gongshang University and constitutes a single-site sample; accordingly, no claims of broad generalisability will be made, and this limitation will be explicitly acknowledged in the limitations section. Reliability refers to the consistency of measurement. This study employs adapted scales from established research and conducts reliability testing through Cronbach's α coefficients, to ensure the internal consistency of each scale. Objectivity refers to ensuring that findings are not influenced by researcher subjectivity. Standardised questionnaires and statistical methods are used, and transparency is maintained throughout the analytical process, in order to minimise the intrusion of researcher subjectivity.

At the same time, this study adopts the criteria proposed by Lincoln and Guba (1988) to ensure the trustworthiness of the qualitative research, encompassing four dimensions: credibility, transferability, dependability, and confirmability. Credibility refers to the degree to which findings faithfully reflect participants' experiences. I will employ member checking, sharing preliminary findings with a subset of participants and inviting them to confirm the accuracy of the interpretations. Transferability refers to the applicability of findings to other contexts. This study will provide thick description, detailing the research context, participant characteristics, and research process, so that readers may judge for themselves whether the findings are applicable to their own settings. Dependability refers to the consistency and traceability of the research process. I will retain complete coding records and analytical memos, and clearly document each research decision, to ensure that the research trail can be retraced. Confirmability refers to the degree to which findings are grounded in the data rather than in researcher bias. Furthermore, I will employ researcher reflexivity, explicitly stating the researcher's own background and potential biases in a positionality statement. Multiple coding will also be adopted, with at least two coders independently coding a portion of the interview data, and inter-coder agreement will be calculated, to enhance the objectivity of the findings.

IV. ETHICAL CONSIDERATIONS

This study will strictly adhere to the Economic and Social Research Council (ESRC) Framework for Research Ethics, as well as the relevant ethical review requirements of Zhejiang Gongshang University and the University of Sussex. Informed consent is the cornerstone of ethical research, and this study will uphold the following informed consent principles at every stage of data collection. The principle of adequate information: participants will be fully informed of the research purpose, data usage, confidentiality measures, the right to withdraw voluntarily, and potential risks. The principle of ensured comprehension: an informed consent form will be provided on the first page of the questionnaire and before the interview, and participants may ask questions for clarification. The principle of voluntary participation: participants will be explicitly informed that they may withdraw at any time, without giving a reason, and that this will not affect their academic assessment. The principle of ongoing consent: during the interview, the researcher will remain continuously attentive to the participant's comfort level, and the participant may terminate the interview at any time.

The text of the informed consent form (provided on the first page of the questionnaire or before the interview) is as follows: "This study aims to understand the strategies and experiences of postgraduate students when using AI (such as ChatGPT, DeepSeek, etc.) to complete English academic tasks. Your participation is entirely voluntary. You have the right to withdraw at any time, without providing any reason, and this will not affect your course grades or academic assessment. All data will be anonymised and used solely for academic research. Research findings will be presented in aggregated form, and no individual will be identifiable. If you have any questions, please contact the researcher: Frank Liu (zl478@sussex.ac.uk)." For the questionnaire survey, clicking "Agree" and proceeding to answer constitutes informed consent. For the interview, the researcher will ask the participant to sign an electronic or paper informed consent form before recording begins.

This study adopts multiple layers of measures to ensure participants' privacy and data security. With regard to anonymisation, the questionnaire does not collect directly identifying information such as names

or student ID numbers, and pseudonyms will be used in place of real names during interviews. With regard to data storage, data will be stored in encrypted form on the researcher's personal computer (password-protected) and on the University OneDrive (compliant with data protection requirements). With regard to data access, only the research team (myself, my supervisors Dr Emily Danver and Dr Keith Perera) will have access to the raw data, and all team members will sign confidentiality agreements. With regard to data retention, data will be retained for five years after the completion of the study (in accordance with academic journal data retention requirements), after which they will be permanently deleted. With regard to the handling of quotations, pseudonyms will be used in reports, and information that could potentially identify individuals (such as specific supervisors, course names, or research project titles) will be removed.The data management plan is as follows. Questionnaire data, collected via Wenjuanxing, will be stored as encrypted Excel files and backed up to OneDrive, retained for five years, then permanently deleted. Interview recordings, collected via recording devices, will be stored as encrypted audio files and backed up to OneDrive, retained for five years, then permanently deleted. Interview transcripts, generated through manual transcription, will be stored as encrypted Word files and backed up to OneDrive, retained for five years, then permanently deleted. Coding and analysis files, generated through NVivo or SPSS, will be stored as encrypted project files and backed up to OneDrive, retained for five years, then permanently deleted.

Given that this study involves AI use, which may touch upon the sensitivity of academic integrity, the research team will adopt the following measures. First, clarifying the research stance. The informed consent form will explicitly state that the purpose of this study is to understand postgraduates' authentic AI use behaviours in real learning situations, not to investigate academic misconduct, and that participants' responses will not be used for any academic disciplinary investigation. Second, information confidentiality. The research team undertakes not to disclose participants' identities or specific usage details to any third party, including supervisors, departments, or university administration. If a participant voluntarily mentions possible academic misconduct during the interview, the researcher will not pursue further questioning and will inform the participant that "you may choose not to answer." Third, limiting the scope of data. This study will collect only participants' self-reports of AI use behaviours (e.g., "I let AI translate") and their subjective evaluations of AI use effectiveness (e.g., "AI helped me solve grammar problems"). This study will not collect the specific content of AI conversations (unless the participant explicitly consents), participants' course assignments or original papers, or any direct evidence that could be used to trace academic misconduct. Fourth, handling sensitive information. If a participant voluntarily discloses behaviour during the interview that could constitute academic misconduct (e.g., "I directly copied an entire AI-generated passage without modification"), the researcher will: not probe for specific details (such as course names or assignment titles); reaffirm anonymity protection but not promise "absolute immunity" (in the case of serious violations, institutional policies will apply); and advise the participant to review the interview quotations before publication.

Furthermore, this study will be submitted to the following bodies for ethical review prior to data collection. The primary ethical review body is the University of Sussex and the Zhejiang Gongshang University Ethics Review Committee, responsible for the main review, as the research is conducted in China with Chinese students as participants, thus requiring approval from the Chinese side. I am also a registered student at the University of Sussex, satisfying UK ethical requirements. The approximate ethical review timeline is as follows: Weeks 1−2, preparation of ethical review application materials; Week 3, submission for Chinese ethical review; Weeks 4−6, awaiting the review outcome (typically requiring 2−4 weeks); if revisions are required, Week 7, revision of materials according to feedback; Week 8, ethical approval obtained and data collection commences. Post-approval reporting obligations include: any substantial changes to the research protocol must be resubmitted for ethical review; any ethics-related incidents (such as participant complaints or data breaches) must be reported to the Ethics Committee within 24 hours; and upon completion of the study, a final ethics report must be submitted.

V. RESEARCHER POSITIONALITY AND SUBJECTIVITY STATEMENT

My academic background is that of a doctoral student in Education and Social Work. It should be specifically noted that I do not have an engineering disciplinary background, nor am I a student or faculty member at Zhejiang Gongshang University. In terms of language, I am a native Chinese speaker and use English as a second language. This linguistic identity bears a degree of similarity to that of the research subjects−Chinese engineering postgraduates who use AI to complete English academic tasks−which facilitates empathic understanding of the difficulties and anxieties participants experience during L2 writing. At the same time, however, I am not an insider within the engineering discipline, and therefore my understanding of the specific conventions, task types, and disciplinary culture of engineering academic writing may reflect a certain outsider perspective.I acknowledge that my personal background and prior

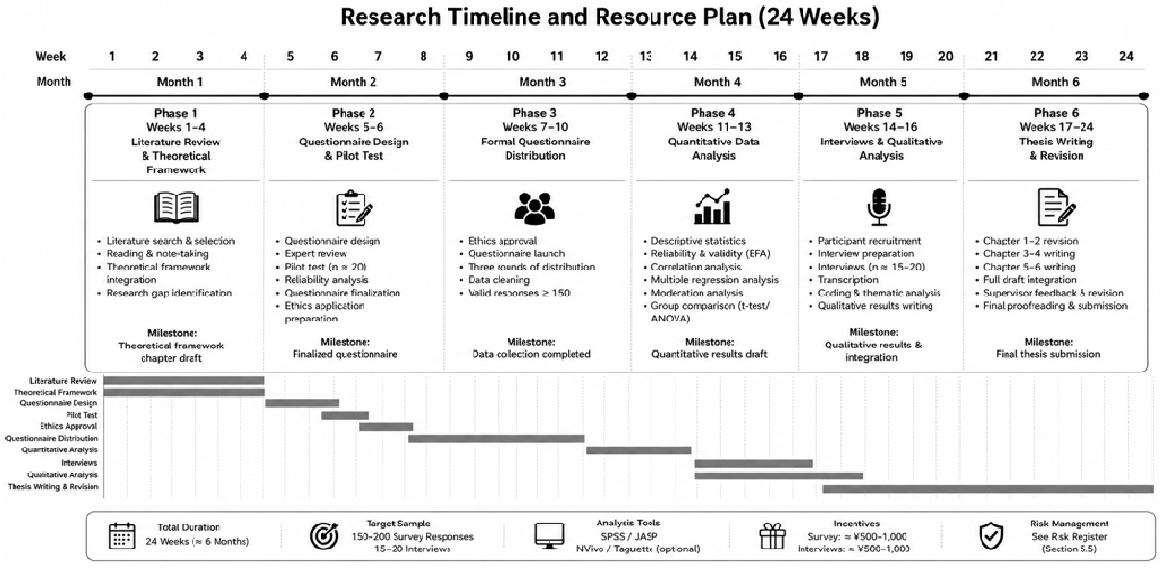
experiences may have a potential influence on various stages of this study, and that ongoing reflexivity must be maintained throughout the research process. First, my pre-understanding of the concept of "anxiety" may influence data interpretation. As an L2 English user, the researcher has personally experienced language anxiety during the learning process. While this personal experience facilitates empathic understanding of participants' experiences, it may also lead the researcher to pay disproportionate attention to anxiety-related expressions during interviews or data analysis, while relatively neglecting other potentially more important factors. To address this potential bias, this study will adopt a multiple coding strategy in the qualitative analysis and retain complete coding records and analytical memos, ensuring that conclusions are drawn from the data itself rather than from the researcher's intuition or presuppositions.

Second, my personal experience with AI use may influence the questionnaire design and the direction of the interviews. I have a certain level of experience using AI tools and a fairly concrete understanding of AI's functions and limitations. This experience is helpful in designing questionnaire items and interview questions that are more targeted and relevant to real-world practice, but it may also lead the researcher to unconsciously presuppose that participants' usage patterns resemble their own, thereby overlooking AI use behaviours or strategies not covered by the researcher's personal experience. To mitigate this bias, the questionnaire and interview guide will undergo content validity checks prior to formal use, by inviting three to five engineering postgraduates to trial the questionnaire or pilot the interview, to ensure that the items cover the diverse AI use practices of engineering students in actual learning situations, rather than being limited to the researcher's personal usage habits.

Third, I do not have an engineering disciplinary background, nor have I studied or taught at Zhejiang Gongshang University. This "outsider" status facilitates a degree of objective distance during the research process, reducing the assumptions and blind spots that may arise from familiarity with the research subjects. However, it may also result in a less thorough understanding of the academic writing conventions, task requirements, and disciplinary culture specific to engineering. To compensate for this limitation, I will actively invite feedback from engineering postgraduates during the questionnaire design and interview process, and at the data analysis stage will rely on participants' own descriptions and interpretations to understand AI use behaviours in the context of engineering writing, avoiding inappropriate inferences based on the researcher's own disciplinary experience.

VI. TIMELINE AND RESOURCES

This study is planned to last approximately six months (24 weeks) and is divided into six stages, with buffer time built in between stages to accommodate possible delays. The overall timeline is consistent with the typical cycle for master's or doctoral thesis research. The following figure sets out in detail the timeline, specific tasks at each stage, resource requirements, and potential risks with corresponding mitigation strategies.



Stage 1 (Weeks 1−4): Literature review and theoretical framework construction. The main task of this stage is to systematically review relevant literature in the fields of AI-assisted writing, L2 writing anxiety, and self-regulated learning, culminating in a clearly defined theoretical framework in its final form.

Required resources include access to literature databases (such as Web of Science, Google Scholar, CNKI) and reference management software (such as Zotero or EndNote). The potential risk is incomplete literature coverage, which may result in the omission of key studies. The mitigation strategy is: regularly consulting with supervisors on literature search strategies, using multiple combinations of keywords for cross-searching, and consulting the reference lists of highly cited works for retrospective supplementation.

Stage 2 (Weeks 5−6): Questionnaire design and pilot testing. The main task of this stage is to complete the initial draft of the questionnaire guided by the theoretical framework, and to conduct two rounds of pilot testing (content validity check and preliminary reliability check), culminating in a finalised questionnaire. Required resources include a Wenjuanxing platform account and pilot participants (3−5 for content validity, 20−30 for reliability testing). The potential risk is insufficient reliability for some items (Cronbach's $\alpha < 0.70$). The mitigation strategy is: after pilot testing, calculating reliability coefficients for each scale, and deleting or revising items with unacceptably low reliability; if necessary, adding supplementary items and conducting an additional pilot test.

Stage 3 (Weeks 7 − 10): Formal questionnaire distribution and data collection. The main task of this stage is to distribute the questionnaire through online channels (WeChat/QQ groups, supervisor recommendations, course groups), with a target of collecting at least 150 valid responses. Required resources include the Wenjuanxing platform, questionnaire completion incentives (a prize draw for small electronic gift cards), and contacts to assist with promotion. The potential risk is an insufficient sample size (fewer than 150 valid responses). The mitigation strategy is: monitoring the response rate regularly during the distribution period; if the target has not been reached by the end of Week 9, expanding distribution through more course groups or requesting supervisors to forward the questionnaire to a wider audience. In addition, the target sample size has been set at 150−200 (above the minimum requirement of 92) in advance, leaving a buffer for data cleaning.

Stage 4 (Weeks 11−13): Quantitative data analysis. The main task of this stage is to clean the collected questionnaire data and conduct descriptive statistics, reliability and validity testing, hypothesis testing (correlation analysis, regression analysis, moderation effect analysis), and supplementary analysis (t-tests, ANOVA), culminating in quantitative results. Required resources include statistical software (SPSS 27.0 or JASP) and reference books on data analysis. The potential risk is that the hypotheses are not supported (e.g., no significant positive correlation is found between delegation behaviour and difficulty alleviation). The mitigation strategy is: reporting the results faithfully regardless of whether the hypotheses are supported, and interpreting them in the discussion section with reference to the qualitative data (Stage 5); non-significant findings also carry academic value, as they may reveal the boundary conditions of relationships between variables.

Stage 5 (Weeks 14−16): Interviews and qualitative data analysis. The main task of this stage is to conduct purposive sampling based on the quantitative findings, to carry out one-on-one online interviews (approximately 10−15 participants), and to conduct thematic analysis of the interview transcripts, culminating in qualitative results. Required resources include recording equipment, transcription software or services, NVivo or MAXQDA analysis tools, and interview participant incentives. The potential risk is difficulty in recruiting interview participants. The mitigation strategy is: at the time of questionnaire collection, inviting participants who are willing to be contacted for a follow-up interview to leave their contact details (collected separately from the questionnaire data), thereby establishing a reserve interview pool; if recruitment numbers are insufficient, snowball sampling can be used, whereby those already interviewed recommend other suitable candidates.

Stage 6 (Weeks 17−24): Thesis writing and revision. The main task of this stage is to integrate the quantitative and qualitative findings, and to complete the writing, revision, and finalisation of all thesis chapters. Required resources include word processing software (Word/LaTeX), reference management software, and supervisor feedback. The potential risk is poor time management leading to delays. The mitigation strategy is: at the beginning of Stage 6, formulating a detailed weekly writing plan with staged deadlines for each chapter; meeting regularly with supervisors to obtain feedback, thereby avoiding extensive revisions caused by misalignment of direction; and maintaining 1−2 weeks of buffer time between stages to absorb any delays that may have arisen in earlier phases.

Overall, the timeline for this study takes full account of the logical progression between stages (literature → instrument → data collection → quantitative analysis → qualitative analysis → writing) and sets out risk mitigation measures at key junctures. The inclusion of buffer time gives the plan a degree of flexibility and adaptability, enabling all research tasks to be completed in a reasonably robust manner within the six-month research cycle.

VII. LIMITATIONS OF THE STUDY

Every study has its limitations, and honestly identifying and discussing these limitations does not

diminish the value of the research. This study has several limitations relating to sample selection, research design, data collection methods, and task types.With regard to sample limitations, this study focuses solely on engineering postgraduates at Zhejiang Gongshang University, a single institutional source, which limits the generalisability of the findings to other institutions, other regions, and other types of students. To address this, the study will explicitly acknowledge the singularity of the sample source in the limitations section of the thesis, refrain from making excessive claims of generalisability, position the research as an exploratory study aimed at revealing phenomena and relationships within a specific context, and provide rich "thick description" detailing the research context, participant characteristics, and institutional setting, thereby allowing readers to judge for themselves the transferability of the findings.With regard to research design limitations, this study adopts a cross-sectional design, with all data collected at a single point in time. While this design can reveal correlations between variables, it cannot establish causal relationships. Accordingly, this study will use causal language cautiously when reporting results, employing terms such as "associated with,""correlated with,""predicted by," and "moderated by." For example, it will state that "delegation behaviour is positively correlated with difficulty alleviation" rather than "delegation behaviour caused difficulty alleviation." In the discussion section, qualifiers such as "may,""perhaps," and "suggests" will be used to avoid over-inference.With regard to data collection limitations, this study's data rely primarily on participants' self-reports, which may be subject to social desirability bias (participants tending to report behaviour that conforms to social expectations), recall bias (participants finding it difficult to accurately recall past AI use behaviour), and metacognitive bias (participants potentially overestimating or underestimating their frequency of strategy use or degree of difficulty alleviation). To mitigate these biases, this study adopts anonymisation to reduce social desirability pressure; employs multi-source triangulation through questionnaires, open-ended questions, and interviews; and, within the questionnaire, asks participants to focus on their "most recent" academic task, while requesting specific examples during interviews to reduce recall bias.With regard to the research design, this study does not include a "no-AI-use" control group. This is primarily because, at present, virtually all students are using AI, and finding a completely AI-free control group would be neither realistic nor ethical. However, this also means that the study cannot compare the effects of "using AI" versus "not using AI." To address this, the study shifts the core question from "Is AI effective?" to "How can AI be used more effectively?" It positions itself as a "strategy difference study," comparing the relationships between different AI use strategies and difficulty alleviation, and avoids drawing conclusions that "using AI is better than not using AI."With regard to task type limitations, the L2 academic tasks engineering students face are diverse, including laboratory reports, literature reviews, dissertations, PowerPoint presentations, academic emails, and data descriptions. Including all these tasks in the analysis without differentiation may lead to a coarsening of the research findings. To address this, the study includes "task type" as a control variable, uses ANOVA to compare differences in strategy use and difficulty alleviation across different task types, and conducts sensitivity analyses by examining relationships within sub-samples of different task types, in order to verify the robustness of the findings.

Overall, the design of this study represents the best feasible choice under real-world constraints. While the above limitations exist, through their explicit identification and appropriate mitigation strategies, the study's conclusions remain of theoretical value and practical significance.

VIII. CONCLUSION

In terms of theoretical significance, this study makes several contributions. First, it extends Self-Regulated Learning theory from traditional learning environments to the context of AI-assisted L2 academic tasks, offering a new theoretical lens for understanding students' strategic learning in the AI era. Second, it proposes a three-dimensional model of AI use strategies—planning, delegation, and verification—operationalising AI use strategies into three measurable dimensions and providing a reusable measurement framework for subsequent research. Third, it repositions anxiety from a core dependent variable to a moderating variable, shifting the focus to "difficulty alleviation." Existing research has often treated "reducing anxiety" as the core goal of AI-assisted writing, a positioning that may deviate from students' actual motivation for using AI: their primary goal is to complete tasks, not to manage emotions. By treating L2 writing anxiety as a moderating variable and focusing on the more immediate goal of "task difficulty alleviation," this study offers a new variable configuration for AI-assisted writing research. Fourth, it fills a gap in the literature on engineering students' L2 academic tasks. Existing research has largely focused on the "academic writing" of humanities and social sciences students, while the diverse tasks faced by engineering students have long been neglected. By proposing the concept of "L2 academic tasks" and expanding the scope of investigation beyond traditional "academic writing" to encompass the output types that engineering students actually encounter, this study lays a conceptual foundation for subsequent research in this area.

In terms of practical significance, this study offers actionable guidance for three groups. For engineering postgraduates, it recommends that students use AI before writing to understand task requirements, break down structures, and formulate plans (planning behaviour); delegate lower-order tasks such as translation, polishing, summarising, and data description to AI, in order to free cognitive resources for higher-order thinking (delegation behaviour); and, at the same time, reminds students not to blindly trust AI output but to actively check, verify, and revise AI-generated content (verification behaviour). For postgraduate English language teaching, it recommends incorporating AI strategy training into the curriculum, adding a teaching module on "how to use AI effectively" into postgraduate English or academic writing courses, and providing differentiated strategy guidance based on students' AI literacy and anxiety levels: highly anxious students may need more guidance on delegation, while less anxious students may need more training in verification. It also recommends a shift from simply "banning AI use" to "teaching students how to use AI responsibly." For AI tool designers, it suggests that AI tools could provide strategy prompts based on user behaviour (e.g., "Would you like to check the references generated by AI?"), design lightweight anxiety-sensing features to offer additional guidance or encouragement when users may be in a high-anxiety state, and provide personalised usage recommendations based on users' AI use strategy patterns.This study seeks to take one step forward from existing research: not simply repeating the question of "Is AI useful?" but pursuing the question of "How can AI be used more effectively?"; not examining "academic writing" in a generic sense, but focusing on the "L2 academic tasks" that engineering students actually face; not discussing "anxiety" in vague terms, but positioning it as a moderating variable and shifting the focus to "difficulty alleviation."

Based on the findings and limitations of this study, future research may proceed in the following directions: adopting longitudinal designs or diary methods to track changes in students' AI use strategies over time and to examine causal relationships; employing quasi-experimental designs to test whether strategy training can effectively enhance difficulty alleviation; conducting multi-centre cross-sectional studies across different Sino-foreign cooperative education institutions to verify the generalisability of this study's findings; focusing on specific task types, such as laboratory reports, and conducting in-depth analyses combining focused questionnaires, logs, and interviews; and developing an L2 writing anxiety scale for the AI era that captures new forms of anxiety such as "meta-anxiety." In an era of rapid AI technological advancement, the very nature of academic writing is undergoing profound change. Understanding how students adjust their strategies, overcome difficulties, and maintain cognitive autonomy amidst this transformation is not only an important topic for academic research, but also a mission for higher education in our time. This study hopes to make a modest contribution towards that end.

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