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How does social support detected automatically in discussion forums relate to online learning burnout? The moderating role of students' self-regulated learning

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ABSTRACT

Engaging students in online discussion forums with social support holds significant potential for preventing and alleviating student burnout. However, the mechanisms by which different types of social support influence learning burnout remain poorly understood. Additionally, existing methods for detecting social support detection are limited in both practical application and theoretical advancement. This study addresses these gaps by developing a robust text classification model for social support and examining its effects on online learning burnout among learners with varying levels of self-regulated learning. We first developed a robust natural language processing model based on bidirectional encoder representations from transformers - bidirectional long short-term memory (BERT-Bi-LSTM) framework, trained on 11226 manually labeled posts from various course forums. This model was then applied to classify forum posts from an educational technology course over one semester. Multiple regression analysis revealed that informational support was negatively associated with two dimensions of learning burnout: emotional exhaustion and improper behavior, and emotional support was negatively correlated with emotional exhaustion and a low sense of achievement. Moreover, a moderating effect analysis indicated that self-regulated learning moderated the negative associations between informational support and improper behavior, as well as between emotional support and emotional exhaustion, with stronger effects observed among learners with lower self-regulated learning. These findings contribute to advancing automated content analysis of social support and provide actionable insights for mitigating student burnout through targeted social support.

1. Introduction

Online education has become widely adopted globally with the advancement of information and communication technologies.

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Amid the COVID-19 epidemic, online learning, with its unique advantages in resource sharing and interaction across time and space, has become increasingly normalized and large-scale (Alon et al., 2023). However, in contrast to face-to-face learning, the temporal and spatial separation of online environments could result in a deficit in intimate communication, interaction, and emotional support for learners (Mu & Guo, 2022). This, in turn, may lead to several negative consequences, including reduced persistence and completion rates (Liu et al., 2022). One such consequence is learning burnout, a negative emotion and experience linked to course learning (Peterka-Bonetta et al., 2019). Conceptually, learning burnout is a negative psychological phenomenon, generally associated with a significant decline in engagement and performance (Wang, Tan, & Li, 2020a,b). The definition of learning burnout originates from the general concept of burnout observed in the human services professions (Madigan & Curran, 2021). Burnout syndrome is an individual response to prolonged work-related stress, which gradually develops and can eventually become chronic, leading to health changes (Montero-Marín, 2016). Psychologically, it adversely affects cognitive, emotional, and attitudinal well-being, often resulting in negative behaviors toward work, peers, and one's professional role. While terminology varies across different contexts; for instance, in traditional school settings, it is often referred to as academic burnout or school burnout. Students experiencing learning burnout typically exhibit diminished mood, and a reduced sense of achievement, and spend less time engaging in learning interactions. Lian et al. (2005) used the Academic Burnout Scale (ABS) to classify student burnout into three dimensions: emotional exhaustion, improper behavior, and low sense of achievement. Specifically, learners suffering from burnout may exhibit negative emotional traits such as aversion and depression, behavioral characteristics like a lack of initiative in adhering to study schedules and cognitive aspects such as feelings of inadequacy and low self-esteem. For some students, online learning burnout has emerged as a significant obstacle hindering their academic development and personal growth. In this context, the discussion forum, a prominent component of online courses, serves as a channel for peer support and information exchange. It allows learners to discuss course content, share opinions, and establish relationships with their peers (Galikyan et al., 2021; Jeng et al., 2023), which can help to alleviate feelings of burnout to some extent. More importantly, it plays a crucial role in cultivating social support, a factor that is usually neglected in e-learning (Hu et al., 2023).

In educational settings, social support refers to behaviors through which students engage in interactions to offer, perceive, or receive emotional attention, instrumental assistance, or informational guidance (Mishra, 2020). Specifically, emotional attention entails the expression of understanding, trust, encouragement, empathy, and caring from teachers and peers; instrumental assistance refers to tangible or material support for learning, such as offering equipment or financial aid; informational guidance involves sharing information, knowledge or suggestions about learning methods or strategies (Cho et al., 2023; Liu & Li, 2023). In a technology-mediated learning community, informational support and emotional support have been identified as crucial elements (Wang, Tan, & Li, 2020a,b). In online discussion forums, receiving social support enables learners to connect with others who share similar experiences and gain understanding and feedback on the challenges they encounter (Pan et al., 2020). Effective social support can assist learners in coping effectively with learning problems and alleviating stress, thereby exerting a significant impact on their learning burnout (Maymon & Hall, 2021; Ye et al., 2021).

Researchers have examined the connection between overall social support and learning burnout in classroom learning environments (Vayre & Vonthron, 2017; Wang, Tan, & Li, 2020a,b). However, within these settings, it can be challenging to capture and identify specific types of social support and their distinct relationships with learning burnout, making it difficult to provide theoretical support for targeted burnout intervention. In online environments, the exchange of social support can be tracked and recorded through digital platforms, enabling the analysis of specific types of social support (e.g., emotional support and informational support) and their critical roles in the learning process. In practice, this involves analyzing the content of discussion forum posts during the exchange of social support and further investigating its relationship with learning burnout. Previous studies have investigated the connection between social support and learning status in distance learning settings, including student engagement, and behavior intention (Barratt & Duran, 2021; Hsu et al., 2018). Nevertheless, the relationship between different types of social support in online forums and learners' burnout remains unclear. Understanding this relationship is crucial for the following reasons. First, by examining specific types of social support rather than treating it as a unified concept, this study uncovers the unique roles that different forms of social support play in online learning contexts. Then, it can provide insights into reducing learning burnout through social interactions, enabling teachers to provide targeted social support that addresses learners' psychological needs effectively. Finally, it lays a theoretical foundation for designing personalized and effective learning support systems that match learners with appropriate social support, thereby enhancing their engagement and well-being in online environments. In addition, researchers generally used traditional methods like surveys, interviews, and manual coding to detect social support in the discussion forum (Smedley et al., 2015). However, given that an online learning community can host hundreds or even thousands of learners and discussion posts, relying entirely on manual analysis can be time-consuming and impractical. Therefore, this research aims to overcome these limitations by applying data mining and deep learning models to process learners' posts on a large scale.

Further, the need to address the negative phenomenon in online learning stemming from internal factors has been consistently highlighted in the literature, particularly during COVID-19 (Aguilera-Hermida, 2020). According to social cognitive theory, environments, individual cognition, and behaviors are interactively influenced, and it emphasizes that social factors are always intricately connected with personal cognitive factors, collectively shaping individual behavior (Wagner et al., 2010). In self-directed online learning, characterized by its autonomy and flexibility, learners need to constantly adjust their behaviors, cognitions, and emotions (Li et al., 2023). This process requires effective self-regulated learning strategies, enabling learners to self-monitor and achieve their learning goals (Zhang et al., 2023). Consequently, this study also focuses on learners' self-regulated learning, a pivotal construct in complex cognitive activities. Self-regulated learning is conceptually understood as an active, constructive process in which learners set learning goals and consciously monitor, regulate, and control their cognition, motivation, and behavior, all within the constraints of their goals and the surrounding context (Alvarez [e]t al., 2022). This concept includes the cognitive, metacognitive, and motivational strategies learners use to guide their learning (Jin et al., 2023). Research has indicated a connection between the strength of self-regulated learning and online learning achievement (Xu et al., 2023). Learners with high self-regulated learning abilities can choose appropriate learning strategies and constantly monitor themselves to optimize their learning (Zheng et al., 2020). However, there are very few studies on how self-regulated learning moderates the effect of external sources on learning burnout. In the context of English learning, Liu and Zhong (2022) noted that learners experiencing burnout may turn to self-regulated strategies to cope. Similarly, Hensley et al. (2022) found that learners with underdeveloped self-regulated learning behaviors and strategies are more prone to academic burden and burnout. Additionally, several existing studies have indicated that learners with a higher level of self-regulated learning possess a greater capacity to cope with the learning support they receive, allowing them to complete courses and achieve better academic outcomes (Min & Nasir, 2020). Based on the literature, we argue that self-regulated learning could moderate the associations between social support and online learning burnout.

1.1. The study objective and research questions

The evidence indicates that the current social support detection models still face challenges in automated forum message analysis, which has hindered the advancement of both practice and theory. Additionally, the impact of different types of social support received by students in online forums on learning burnout remains largely unexplored. To address these gaps, this study aims to employ an optimized BERT model, bidirectional encoder representations from transformers - bidirectional long short-term memory (BERT-Bi-LSTM), to automatically detect social support content in discussion forums, and analyze its relationship with learning burnout. Furthermore, we examined how self-regulated learning moderated the aforementioned relationships. This study attempted to address the following research questions.

RQ1. How well are different types of social support received in discussion forums identified by the BERT-Bi-LSTM model?

RQ2. What is the relationship between students' burnout and the social support they received in the discussion forums?

RQ3. How does self-regulated learning moderate the relationships between received social support and online learning burnout?

2. Literature review

2.1. Social support and learning burnout

Social support is a multifaceted concept, categorized based on subjective experience into received social support and perceived social support (Barrera, 1986). It can also be classified by content type into informational, emotional, instrumental, and appraisal support (Malecki & Demaray, 2003). According to the Social Support Behavior Code developed by Cutrona and Suhr (1992), social support includes informational support (provision of advice or opinions on coping with stress), emotional support (expression of love, care, or compassion), esteem support (communication of respect and confidence), tangible support (provision of goods or services), and network support (communication belonging to groups or individuals with similar interests and concerns). The importance of various forms of social support in traditional and distance learning has been repeatedly explored in previous literature (Barratt & Duran, 2021; Elumalai et al., 2021). For instance, Li and Peng (2019) noted that providing emotional, material, and informational support can strengthen an individual's capacity and willingness to engage in particular activities and assist students in coping with challenges. Moreover, social support theory provides a theoretical foundation for understanding the role of social support in psychological well-being, which suggests that individuals are better prepared to manage situations related to illness or other medical issues when they obtain adequate social support (Sendra et al., 2020). Similarly, actual social support behaviors provide learners with assistance in handling various tasks throughout their online courses, creating a positive cycle of enhanced well-being and reduced learning anxiety.

Additionally, in traditional learning, numerous studies have explored the connection between social support and learning burnout. For example, Boren (2014) identified that social support offers people pleasant social interactions, contributing to emotional balance and decreased burnout. The negative association between social support and learning burnout in school education has been consistently revealed in the research conducted by Kim et al. (2018). Despite this, the primary forms of social support—received social support and perceived social support—are not entirely distinguishable in offline learning because the process of social support exchange often occurs in subtle and indirect ways. In this context, the receipt and provision of actual social support are difficult to observe and record, making the measurement of received social support somewhat subjective. Besides, identifying specific types of social support (e.g., emotional support and informational support) and their distinct relationships with learning burnout can be challenging, which complicates providing theoretical support for targeted burnout interventions.

In distance learning contexts, the online platform has become the primary carrier of social support exchange, which makes the process of students providing, seeking, and receiving support more easily traceable. The distinction between perceived and received social support is even more apparent, and social support exchange behavior in the online community becomes the focus of research. For example, by examining the connection between various forms of received social support and the willingness to provide social support, Lin et al. (2015) explored online social support exchange behavior. Hu et al. (2023) investigated the significant positive association between providing social support and perceived social support in e-learning by analyzing the cognitive processes involved in social support exchange. Moreover, the correlation between exhaustion and received social support has been explored in the research conducted by Lo (2019). During COVID-19, Szkody et al. (2021) found that the overall amount of social support received by college students was positively correlated with their psychological health.

Furthermore, student burnout is closely linked to social interaction behaviors, such as teacher support, and peer feedback (Huang et al., 2023; Yang et al., 2022). Extensive research has also tried to link social support with online learning outcomes, such as learning satisfaction and learners' intention (Hsu et al., 2018; Weng et al., 2015). Some scholars also claim that in technologically enhanced learning environments, learners are less likely to experience burnout when they receive more support from administration and peers (Barratt & Duran, 2021; Zhao et al., 2022). In other words, the quantity of social support that learners receive plays a significant role in alleviating their burnout status. In online learning settings, social support generally includes two types: informational support and emotional support, while other types of support such as tangible support, are difficult to obtain in online environments (Mirzaei & Esmaeilzadeh, 2021). It has been shown that supportive social transactions often mitigate the detrimental effects of emotional exhaustion or negative sentiment (Bedué et al., 2020; Li et al., 2018). Nevertheless, limited studies have examined how online, actual social support affects learners' burnout, and the existing studies considered social support as a general concept rather than investigating the impact of each type of social support. This lack of specificity complicates efforts to clarify the connection between social support and student burnout in online environments. Addressing this gap can offer valuable insights into how different types of social support can be targeted to alleviate student burnout and guide the development of personalized online support systems to boost learner engagement.

2.2. Quantitative content analysis of social support in forums

Forums are the primary channel for social support exchange among online members, and the data they record reflect the quality of online interactions (Johnson et al., 2020; Zou et al., 2021). Currently, several studies across different fields have used manual coding methods to quantitatively analyze social support in forums. For instance, Wang et al. (2021) investigated informational support and emotional support in an online community through quantitative content analysis and found a significant effect of social support and individuals' knowledge contributions. In the research of De Choudhury and Kiciman. (2017), they employed an established social support theoretical model to interpret and code online social support language in social media. Similarly, for a recently launched discussion forum, Smedley et al. (2015) examined the informational support content and the establishment of support processes. Nevertheless, the content analysis method requires expert involvement and is time-consuming, making it challenging to apply in practice.

In recent years, several scholars have investigated the actual online social support received, employing data mining methods for post-analysis in non-educational research. For example, in the research conducted by Deetjen and Powell (2016), all posts in online support forums were classified as informational or emotional using a Bayesian classification algorithm. Similarly, machine learning techniques have been used to detect both informational support and emotional support within the social community (Wang et al., 2015). Additionally, Xing et al. (2018) employed a supervised machine learning model to automatically recognize posts within the community that request and provide informational support. Lately, academics have shifted their focus to the issue of providing social support in online discussion forums based on deep learning models (Li and Xing, 2021), but with a more technical perspective. The above methods have reduced labor costs and enabled automated content detection, but they face significant challenges such as non-robust models and unrecognized words.

Additionally, there are few studies regarding the content detection of social support exchange in online learning settings. During online learning, a virtual social community can be formed as an alternative to in-person social interactions, enabling the expression of fears, sharing of feelings, and exchange of social support (Yan, 2020a,b). The learning behaviors and interactive contents are recorded within this online context. The analysis of a substantial number of social support entries becomes crucial for online learning interventions. Based on previous studies that employed various models to classify texts in online forums (Liu et al., 2022; Zheng et al., 2022), we employed four well-established deep learning models, namely BERT, Bi-LSTM, BERT-Bi-LSTM and Convolutional Neural Networks (CNN), along with two traditional machine learning models including Naive Bayes (NB) and Random Forest (RF), to classify social support texts. These models were chosen for their widespread use in educational research for text classification tasks and have demonstrated promising performance (Huang et al., 2023; Li, Lei, & Ji, 2022; Liu et al., 2022). Research demonstrated that deep learning models excel in automatic feature extraction and effectively capture complex semantic relationships, whereas traditional machine learning models are favored for their computational efficiency and suitability for small datasets (Li et al., 2022b). Specifically, models like BERT, Bi-LSTM, BERT-Bi-LSTM, and CNN are highly regarded for their capacity to encapsulate rich textual semantics and contextual information. In contrast, NB and RF are noted for their efficiency and robustness, particularly when dealing with smaller datasets and high-dimensional feature spaces (Abdullah et al., 2023; Alsaeedi et al., 2024). Furthermore, we also evaluated a variety of other models, ultimately focusing on those best suited to deliver superior performance on our specific dataset. Models that struggled with nonlinear data or complex feature interactions were excluded. For instance, decision trees (DT) and k-nearest neighbour (KNN) were omitted after preliminary experiments showed they performed comparably or worse than the selected models, both in terms of accuracy and computational efficiency (Jasti et al., 2022). Our ultimate goal is to identify the model that delivers the most optimal performance and apply it in further analyses.

2.3. Self-regulated learning in online learning

As an important construct of social cognitive theory, self-regulated learning focuses on learners' self-orientation to achieve learning goals (Sinring et al., 2022). Due to the flexibility, openness, and decentralized characteristics of online learning, learners need to employ more self-regulated learning strategies to guide their learning process (Alvarez et al., 2022). Learners with strong self-regulated learning abilities not only understand task requirements but also choose effective learning strategies, continuously self-monitoring to optimize their learning outcomes (Zhang et al., 2023). When learners receive helpful external resources, such as social support, it triggers the mobilization of internal resources, particularly self-regulated learning, thereby affecting their psychological status. Especially, the planning and reflection process in self-regulated learning can aid learners in selecting useful and appropriate resources to alleviate stress (Yan, 2020a,b). Simultaneously, the quality of learners' internal resources plays a role in shaping their demand for external resources, as highlighted by Min and Nasir (2020). In essence, self-regulated learning plays a pivotal role in promoting the perception of social resources and regulating learners' behaviors and psychological status.

Numerous scholars indicate a positive correlation between self-regulated learning and the perception of social support (Martínez-López et al., 2023) and can lead to the reduction of academic burnout (Räisänen et al., 2020; Wang & Zheng, 2023). However, they seldom take into account the specific contribution that self-regulated learning makes to the association between social interaction and learning burnout. In other words, further investigation is needed to determine whether and how the relationship between social support and learning burnout varies among learners with different levels of self-regulated learning. In a relevant study, Jang and Jeong (2017) pointed out that self-regulated learning moderates the correlation between academic stress and burnout. In the realm of online workplace learning, Lin et al. (2018) found that self-regulated learning moderates the relationship between social support and attitudes toward continued online learning. Emphasizing the significance of individual behaviors, Hermanto et al. (2018) indicated that self-regulated learning moderates the connection between environmental influences and learning outcomes. Furthermore, Jansen et al. (2020) suggested that compared to the control group without any interventions, learners who complied with the self-regulated learning intervention exhibited higher engagement in self-regulated activities. Hence, drawing upon the insights from existing literature and social cognitive theory, we assume that self-regulated learning has a moderating effect on the associations between social support and online learner burnout. The findings will provide theoretical implications for mitigating negative psychological states in online learning from a social-cognitive perspective.

3. Methods

3.1. Research context and participants

In this study, we used a convenience sampling method, recruiting 200 participants (136 women and 64 men) who registered for an Application of Educational Technology course. This sampling approach was chosen for practical reasons, as the course participants were easily managed and actively engaged in the online learning environment. The participants' ages ranged from 19 to 24. Most participants were from the fields of education, psychology, mathematics, and artificial intelligence, all of whom were attending the course for the first time. All participants belonged to the Asian ethnic group, and during the entire research process, there were no instances of biases or discriminatory actions against other racial/ethnic groups. The course was offered by an academic team from a southern China university and was developed on the well-known online course provider, the Chinese University MOOC platform. The course for this study comprised eight content units, focusing on applying modern educational technology in primary education. All participants possessed a minimum of one prior online learning experience, and the course was recommended for those with a foundational understanding of online operations and teaching theory. Before conducting the research, we provided all learners with information about the research purpose and procedures and obtained their consent.

Fig. 1. A discussion thread example in the online forum.

As illustrated in Fig. 1, the learning activities associated with every unit comprised viewing lecture videos and other materials, completing unit tests, and taking part in discussion forums. The course provided a discussion board each week, offering participants a dedicated forum for interaction and seeking assistance, and participation in the discussion forums was optional. To address various learning needs, four forum types were established, namely the course forum, the general forum, the teacher Q&A forum, and the quiz forum. Learners could express any problems experienced, opinions, and feelings about the courses, as well as respond positively to the problems or feelings of others. The topics learners discussed might relate to the course learning, quizzes and exams, and platform operation. Additionally, like most online courses, it is necessary to implement specific strategies to engage learners in online forum discussions (Zou et al., 2021). To facilitate the exchange of social support between learners and to ensure the quality of interaction in the forums, learners were informed before the start of the course about the importance of forum discussions and the criteria for evaluating the quality of posts and replies. Furthermore, the instructor set up several discussion topics designed to encourage students to share their personal views or emotional experiences. For instance, there was a thread dedicated to having students express their expectations, concerns, and fears about embarking on a teaching career. The instructor motivated course participants to engage in forum discussions initiated by both instructors as well as other students. In addition, two teaching assistants who received professional training were responsible for monitoring the behavior of participants in the forum and offering necessary social support.

3.2. Research design

There were four main phases to the research design (Fig. 2). **Phase 1**: Online learners' forum posts reflecting social support and questionnaire data measuring learning burnout, self-regulated learning, and demographics (gender, learning preferences, etc.) were collected, and then stored in the database. **Phase 2**: Data was preprocessed, which included removing invalid data that did not enhance course-related learning, coding social support in forum data, and conducting questionnaire statistical analysis. **Phase 3:** The BERT-Bi-LSTM model was constructed, trained, and assessed using the social support datasets. Then the best-trained model was employed to predict unlabeled forum posts, with each post being encoded with either an informational support or an emotional support label. The first question was explored in this phase. **Phase 4:** Data analysis methods, such as multiple regression analysis and moderating effect analysis, were used to resolve the second and third questions.

Specially, in **Phase 1**, the forum data collected consisted of two parts (labeled dataset D1 and unlabeled dataset D2), one part was for building the classification model, and the other was used to apply the predictive model. Firstly, to develop an effective model for classifying social support, we gathered 11, 226 posts from three additional courses (D1) from January 2020 to June 2020. These courses included "Teaching Application of Mind Mapping" "Artificial Intelligence for Education" and "Smart Classroom Teaching". The selection of these three courses was based on their large learner communities and diverse social support texts, which supported the construction of more robust models. Additionally, the content of the three courses focused on teaching and learning, similar to the aforementioned target course. As for the data used to apply the predictive model, the forum data on social support from 200 learners recruited in Section 3.1 was included (D2). Furthermore, in **Phase 3**, after analyzing the labeled dataset D1, we discovered that social

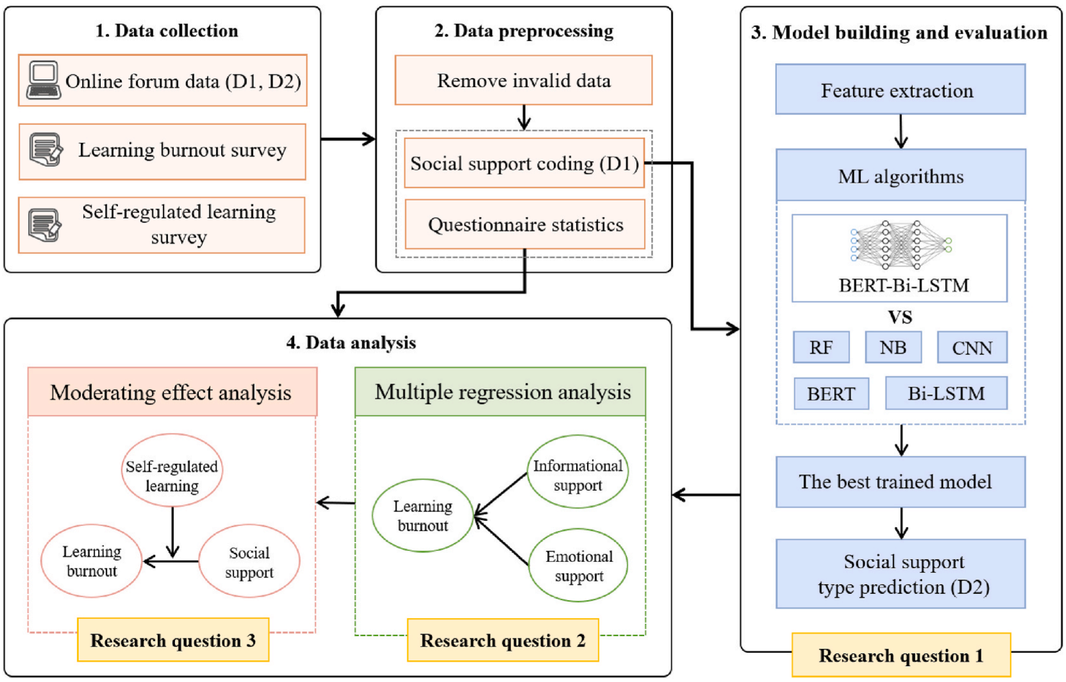

Fig. 2. Research design.

support in an online forum was mainly long text data, containing combinations of multiple word categories (e.g., verb, adjective, and adverb). Thus, we assumed that a model considering contextual information and capable of extracting multiple semantic features would be more suitable for the classification of social support. Furthermore, in previous studies, an optimized BERT model, BERT-Bi-LSTM, demonstrated advantages in acquiring domain knowledge and focusing on significant words within the context (Shobana & Murali, 2023; Wankhade & Rao, 2022). Hence, this study employed the BERT-Bi-LSTM model to extract and fuse the linguistic features and conducted comparative experiments to validate the model hypothesis.

3.3. Measures

3.3.1. Post coding for social support

In **Phase 2**, we gathered posts from peers and instructors that involved emotional care and informational support to quantify the received social support. These posts mainly occurred when learners encountered problems and asked for help. Once the thread initiated by a learner received responses from others (teachers/learners), the learner was socially supported. In other words, the number of posts received by students represented, to some extent, the level of attention they received from different individuals within the community. In this study, we primarily collected responses to threads initiated by learners in discussion forums and excluded the responses that did not enhance course-related learning from the dataset. To enhance the quality of the datasets employed for model development, posts that lacked informational guidance or emotional connection in the content related to learning and platform usage for online courses, such as “Hehe”, “I’m coming” or “Don’t know”, were manually excluded. Therefore, all posts included in the subsequent coding and analysis were considered instances of social support.

We analyzed the content of forum posts using the coding tool developed by Cutrona and Suhr (1992), which was further adapted to suit the online learning context (see Table 1). The coding framework includes five types of social support: informational support, emotional support, esteem support, tangible support, and network support. Among these, informational support and emotional support were found to be the two most frequently exchanged types of support online (Mirzaei & Esmaeilzadeh, 2021; Wang, Tan, & Li, 2020a,b) and were the focus of analysis in the present study. Additionally, informational and emotional support encompass a wide variety of content and are presented in diverse forums. For example, informational support includes suggestions/advice, referrals, situation appraisal, and sharing experiences. Emotional support consists of relationships, expression of caring, understanding/empathy, and encouragement. Therefore, when conducting specific coding, coders first clarify the subcategories of social support to ensure more accurate coding, and then categorize the support as informational support (IS) or emotional support (ES). Drawing on existing research, data were encoded at the level of entire messages rather than individual sentences within posts, enabling the evaluation of posts containing a primary social support category (Da Moura Semedo et al., 2023). In other words, when posts include multiple types of support, the predominant type of social support is assigned as the final social support label. For example, the post “I have the same expectations as you, but this course primarily focuses on knowledge of educational technology and is less involved in innovative teaching” was labeled as informational support, as it mainly provides information about the course content, despite containing elements of emotional support.

During the coding process, two coders first independently encoded a randomly selected set of 100 posts, analyzed discrepancies in the samples and revised the coding scheme accordingly. Then, two coders jointly coded 300 messages to verify the applicability of the coding scheme. The estimated Cohen’s kappa coefficient for coding reliability was .89 ($p < .001$), 95% CI [.83, .95], indicating a very high level of agreement (McDonald et al., 2019). Finally, two coders labeled the remaining posts as “Informational support (IS)” or “Emotional support (ES)”. In total, the manually labeled dataset D1 included 3094 posts in the emotional support category and 8132 posts in the informational support category.

3.3.2. Online learning burnout

The 200 participants recruited completed a questionnaire survey during the last week of the course, which was designed to measure online learning burnout, self-regulated learning, and demographics. We utilized the Chinese version of the Academic Burnout Scale (ABS), which includes 20 questions across three dimensions (Lian et al., 2005): emotional exhaustion, improper behavior, and low sense of achievement. For example, the item “I feel exhausted every time I finish this course.” was included to assess emotional exhaustion, the item “When taking this course, I rarely plan my study time” was included to measure improper behavior, the item “It is easy for me to master the knowledge of this course” was included to evaluate the low sense of achievement. Higher scores indicate a greater degree of online learning burnout. Because this scale is typically used to measure normalized burnout in learning and is not specific to a particular course, we made necessary modifications to adapt it to the online learning environment. The scales of online

Table 1
Sample post coding for social support.

Post	Label
Do not be sad, there’s another chance in September. I can understand your situation.	(ES) Emotional support
It is better to use the computer to operate. I learned so many courses but have never been able to upload successfully using mobile phones.	(IS) Informational support
Your question is on the record. I will put your question at the top first. Do not worry.	(ES) Emotional support
I couldn’t agree more! It speaks to my heart!	(ES) Emotional support
As for the electronic whiteboard, you can learn this course, which may help you: https://www.icourse163.org/course/icourse-1001554015.	(IS) Informational support

learning burnout used in this study had high reliabilities, with a Cronbach's alpha coefficient of .89 for the overall survey. The reliability for the emotional exhaustion subscale was .85, .72 for the improper behavior subscale, and .73 for the low sense of achievement subscale.

3.3.3. Self-regulated learning

The measurement for self-regulated learning was based on the online self-regulated learning questionnaire (OSLQ) developed by Barnard et al. (2009) and demonstrated excellent reliability and validity. The 24-item scale, with Cronbach's coefficient of .93, consisted of six subscales: goal setting, time management, environment structuring, task strategies, help-seeking, and self-evaluation. Both the measurements of learning burnout and self-regulated learning utilized a 5-point Likert scale, with 1 indicating strong disagreement and 5 indicating strong agreement.

3.3.4. Demographics

To control for the effects of several factors on learning burnout, learners were asked to report their genders and learning preferences. Learners' learning preferences were assessed by asking them the following question: "Do you prefer online learning or offline learning?".

3.4. Data analysis

To maintain data integrity, the subsequent analysis excluded the students who did not respond to the survey or did not receive social support due to a lack of participation in forum discussions. Of the 200 students recruited, 194 responded to the questionnaire survey, and 165 received social support through the discussion forum. Among the students who did not complete the survey, 4 did not receive social support either. Consequently, 37 students were excluded from the analysis. Frequency analysis conducted on the remaining sample's variable data using SPSS revealed no instances of missing data. Hence, the final sample comprised 163 learners. The power analysis results indicated that 43 samples were required to achieve a statistical power of .80. Therefore, the sample size employed in this study was sufficient for the proposed model. The number of distinct types of social support entries was calculated separately and then aggregated at the individual level. In this way, each learner had the number of different types of social support received as well as the corresponding values for different dimensions of learning burnout.

To answer the first research question, we evaluated the effectiveness of both traditional machine learning and deep learning models. The BERT-Bi-LSTM was compared with five baseline models, such as RF, NB, CNN, BERT, and Bi-LSTM. To maximize the performance of the models, we configured traditional machine learning models (e.g., RF and NB) to employ TF-IDF word feature, while deep learning models (e.g., CNN and Bi-LSTM) utilized Word2vec representations. The detailed configurations of four deep learning methods were as follows. (1) The parameter configurations of CNN included: learning rate, 1e-3; the number of epochs, 11; sequence length, 64; random deactivation dropout, .10; the number of layers, 3; and batch size, 64. (2) The parameter configurations of BERT included: learning rate 1e-4; the number of epochs, 5; sequence length, 50; the number of layers, 13; and batch size, 24. (3) The parameter configurations of Bi-LSTM were as follows: learning rate, 1e-3; the number of epochs, 13; sequence length, 64; the number of layers, 2; and batch size, 64. (4) The parameter configurations of BERT-Bi-LSTM included: learning rate 1e-4; the number of epochs, 5; sequence length, 50; the number of layers, 14; and batch size, 24.

The text-classification model underwent Nested GroupKFold (Berrar, 2019) to enhance the reliability of the constructed model. Nested GroupKFold combines two powerful cross-validation techniques: nesting and group-based splitting. In our approach, both the outer and inner folds are implemented using GroupKFold with $k = 5$. The outer fold assesses model performance, while the inner fold is responsible for hyperparameter tuning. The key advantage of GroupKFold is its ability to ensure that students with the same IDs never appear in both the training and validation sets simultaneously, thus maintaining data independence. When nested, this approach provides additional benefit of unbiased performance estimation, as the hyperparameter tuning process is entirely separated from the final evaluation. This is particularly crucial because it prevents data leakage, which could arise if the same data were used for both hyperparameter tuning and evaluation. The nested structure further strengthens the assessment by considering uncertainty in the hyperparameter tuning process. Compared to traditional KFold, Nested GroupKFold offers stronger data independence by preventing group-level leakage, provides a more realistic performance evaluation by accounting for data grouping characteristics, and enables more robust model selection through its nested structure. After establishing and validating the performance of the text classification model, the next step was to apply the model to the unlabeled dataset D2. At this stage, we also conducted manual coding on the posts in dataset D2 to further validate the classification effectiveness of the prediction model and its transferability across different courses.

Based on the classification results of the social support in online discussion forums by the best classification model, in **Phase 4**, we primarily conducted two steps at the individual learner level to examine the relationship between social support and learning burnout and the moderating role that self-regulated learning plays in this association. First, we performed a multiple regression analysis in which three dimensions of learning burnout (emotional exhaustion, improper behavior, and low sense of achievement) as the dependent variable, learners' gender, learning preferences as covariates, the numbers of informational support and emotional support entry learners received as independent variables. To ensure the reliability of the data analysis, we assessed residual normality and tested for common method bias, auto-correlation, and multicollinearity before performing the regression analysis.

Second, to further analyze the moderating effect of self-regulated learning, we analyzed the interaction effects between the number of different types of social support entries and learners' levels of self-regulated learning on the contribution to online learning burnout. To more clearly illustrate the direction and strength of the moderating effect, learners' levels of self-regulated learning were categorized into lower and higher tiers using the mean $\pm$ standard deviation method in a simple slope analysis. This approach is commonly used for significance testing of continuous moderating variables (Liu et al., 2017). Additionally, a sensitivity analysis was conducted to evaluate the moderating effect at varying thresholds of the moderating variables, ensuring the stability of this effect. This analysis was carried out using the PROCESS macro (version 3.2) developed by Hayes (2018).

4. Results

4.1. How are the different types of social support received in discussion forums identified accurately by the BERT-Bi-LSTM model?

This study evaluated the performance of specific models in social support classification tasks in terms of accuracy, macro-precision, macro-recall, macro-F1, and Cohen's Kappa. The performance results are presented in Table 2. In all indicators, BERT-Bi-LSTM outperformed RF, NB, CNN, BERT, and Bi-LSTM. The study indicated that integrating the text features of social support captured by Bi-LSTM with BERT effectively improved model performance. Therefore, BERT-Bi-LSTM was chosen as the predictive model in the current study.

Unlabeled dataset D2 was classified by a trained BERT-Bi-LSTM model, and each post was labeled "IS" or "ES". To further validate the performance of the prediction model, we also manually coded the posts in dataset D2 and analyzed the agreement between humans and the model coding. The Cohen's Kappa coefficient was .88 with a 95% CI [.86, .90], indicating that the BERT-Bi-LSTM model performed well on the target course in this study. For posts where there was a discrepancy between the machine and human coding, we further verified and finalized the social support type for each post. Of the total posts received by 163 learners in the online forum, 1057 were categorized as IS, and 584 were categorized as ES. Additionally, we validated the transferability of the prediction model based on social support coding rules across different courses using dataset D2. For instance, a post containing the statement "Indeed, both statements emphasize different aspects of micro lecture, but neither is comprehensive and the two cannot be equated." was classified as information support (IS) by the BERT-Bi-LSTM model. The result of classification is correct, as the post provider expresses her/his opinions about the micro lecture to the learners, representing a form of informational support offered to the learners. Moreover, the post "I share the same expectations and concerns as you do. Let's work together to overcome them." was categorized as emotional support (ES) by the classification model. The classification is correct, as the post expresses the learner's understanding of the peer's problem or situation, along with providing encouragement. Therefore, the model trained in this study is applicable to the target course, which is a regular online course in the field of education.

4.2. What is the relationship between students' burnout and the social support they received in the discussion forum?

As demonstrated in the results of the bivariate correlations (see Table 3), statistically significant relationships were found between the two types of social support (emotional support and informational support) and three dimensions of learning burnout. Notably, informational support was also positively correlated with emotional support, as they were two different dimensions of online social support (Tseng et al., 2022).

To assess the importance of specific variables in predicting online learning burnout, we conducted multiple linear regression. We examined the normality of residuals using a normal Q-Q Plot. No common method bias was detected based on Harman's one-factor test, as the explained variance was 39.68%. The Durbin–Watson values for the three regression models were 1.88, 2.04, and 2.09, indicating the absence of auto-correlation issues. The multicollinearity test showed minimal correlation among the independent variables (VIF ranging from 1.01 to 1.28; tolerance ranging from .78 to .99). As shown in Table 4 (models 1 to 2), the emotional exhaustion dimension of learning burnout had significant negative relationships with both informational support and emotional support ($B = -.04$, $p < .05$; $B = -.07$, $p < .01$, respectively). There was a significant negative association between informational support and improper behavior dimension ($B = -.04$, $p < .05$). Additionally, low sense of achievement dimensions was negatively correlated with emotional support ($B = -.06$, $p < .01$). Thus, the higher number of informational support entry learners received, the lower levels of emotional exhaustion and improper behavior. Similarly, the higher the number of emotional support entry learners obtained, the lower their levels of emotional exhaustion and low sense of achievement.

4.3. How does self-regulated learning affect the relationships between received social support and online learning burnout?

Based on the results of multiple regression analysis, a subsequent examination was carried out to investigate the moderating effect of self-regulated learning on the relationship between predictor factors and outcome variables. We employed PROCESS v3.2 Model 1

Table 2
Classification results of social support.

Method	Accuracy	Macro-Precision	Macro-Recall	Macro-F1	Cohen's Kappa	95% CI
RF	.87	.85	.84	.84	.69	[.67, .70]
NB	.77	.74	.80	.75	.52	[.50, .53]
CNN	.89	.87	.85	.86	.72	[.70, .73]
BERT	.90	.88	.89	.88	.76	[.75, .78]
Bi-LSTM	.89	.87	.85	.86	.72	[.70, .73]
BERT-Bi-LSTM	**.91**	**.89**	**.90**	**.89**	**.78**	[.77, .80]

Table 3
Summary of intercorrelations.

	1	2	3	4	5	6
1. Gender						
2. Learning preferences	−.12					
3. Informational support	.16*	−.07				
4. Emotional support	.25**	−.11	.42***			
5. Emotional exhaustion	−.09	.19*	−.29***	−.33***		
6. Improper behavior	−.16*	.34***	−.26**	−.27**	.65***	
7. Low sense of achievement	−.05	.18*	−.19**	−.27**	.55***	.62***

Note. *$p < .05$, **$p < .01$, ***$p < .001$.
Dummy coded: 1 = male, 2 = female.

Table 4
Multiple linear regression results of learning burnout.

Model	Variables	Emotional exhaustion				Improper behavior				Low sense of achievement			
		B	SE	p	R^2	B	SE	p	R^2	B	SE	p	R^2
1	Constant	2.02	.23	.00	.04*	2.35	.22	.00	.13***	2.36	.20	.00	.03
	Gender	−.08	.10	.40		−.14	.09	.12		−.03	.08	.76	
	Learning preferences	.20	.09	.02		.37	.08	.00		.17	.08	.02	
2	Constant	2.08	.22	.00	.16***	2.41	.21	.00	.20**	2.39	.19	.00	.10**
	Gender	.02	.09	.79		−.07	.09	.46		.05	.08	.57	
	Learning preferences	.17	.08	.04		.35	.08	.00		.15	.07	.04	
	Informational support	**−.04**	.02	**.03**		**−.04**	.02	**.04**		−.02	.02	.29	
	Emotional support	**−.07**	.03	**.00**		−.05	.03	.06		**−.06**	.02	**.01**	
3	Constant	3.86	.50	.00	.20***	4.88	.46	.00	.35***				
	Gender	.03	.09	.78		−.03	.08	.75					
	Learning preferences	.15	.08	.06		.32	.08	.00					
	Informational support	−.23	.18	.21		−.37	.17	.03					
	Self-regulated learning	−.50	.13	.00		−.70	.12	.00					
	Informational support × self-regulated learning	.05	.04	.27		**.09**	.04	**.03**					
4	Constant	3.89	.45	.00	.24***					3.60	.40	.00	.18***
	Gender	.07	.09	.41						.08	.08	.32	
	Learning preferences	.13	.08	.11						.12	.07	.09	
	Emotional support	−.46	.19	.02						−.09	.17	.58	
	Self-regulated learning	−.52	.11	.00						−.35	.10	.00	
	Emotional support × self-regulated learning	**.10**	.05	**.03**						.01	.04	.75	

Note. *$p < .05$, **$p < .01$, ***$p < .001$. Bold represents significant values of variables.
Dummy coded: 1 = male, 2 = female.

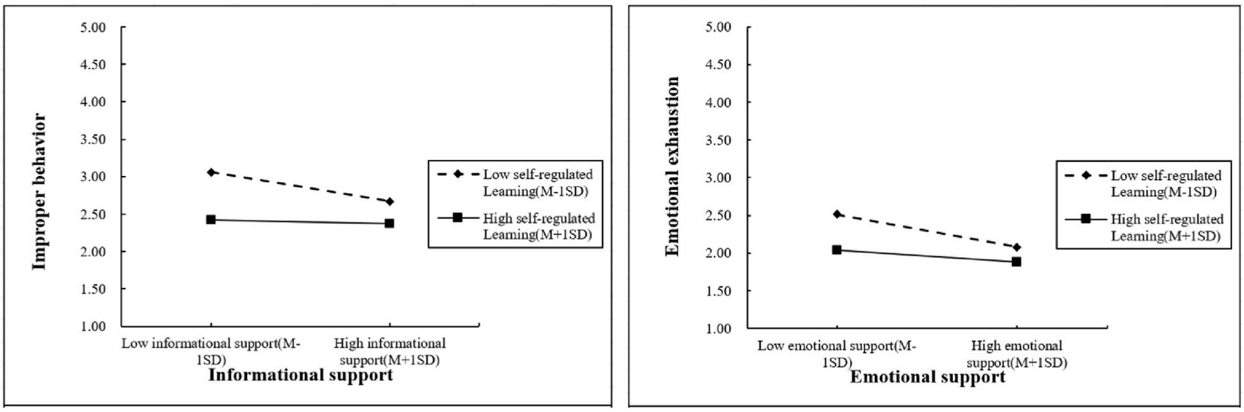

Fig. 3. Moderating effect of the self-regulated learning contributed to the relationship between social support and learning burnout.

by Hayes (2018) and conducted 5000 bootstrapping iterations. Table 4 presents the results (models 3 and 4). The results indicated that self-regulated learning was considered a significant moderator in the association between informational support and improper behavior dimension (B = .09, $p < .05$, CI [.01, .16]), and the association between emotional support and emotional exhaustion dimension (B = .10, $p < .05$, CI [.01, .19]). As demonstrated by simple slope analysis on the left in Fig. 3, the negative effect of the informational support on the improper behavior dimension was stronger at the lower level of self-regulated learning (−.09, [SE = .04], $p < .05$, 95% CI [-.17, −.01]), and no negative effect at a higher level of self-regulated learning (−.01, [SE = .02], $p > .05$, 95% CI [-.05, .03]). Thus, for learners with lower levels of self-regulated learning, the more informational support entries they received, the higher the level of improper behavior in their learning burnout dimensions.

In addition, as shown on the right of Fig. 3, the negative effect of emotional support contributions on the emotional exhaustion dimension was stronger at a lower level of self-regulated learning (−.14, [SE = .04], $p < .01$, 95% CI [-.23, −.05]) and was weaker at a higher level of self-regulated learning (−.05, [SE = .02], $p < .05$, 95% CI [-.10, −.00]). In other words, while more emotional support reduces emotional exhaustion in learning burnout for both groups, its effect is more pronounced for students with lower levels of self-regulated learning. To assess the sensitivity of the moderating effect at different thresholds of the moderating variables, self-regulated learning was categorized into high and low groups based on the mean. Regression analysis was then performed within these subgroups. The findings revealed that the moderating effect of self-regulated learning on the relationship between informational support and improper behavior remained consistent ($p < 0.5$), as did its effect on the relationship between emotional support and emotional exhaustion ($p < 0.1$). Thus, it appears that the level of self-regulated learning moderates the negative correlation between received social support and learning burnout, with a stronger negative effect observed for lower levels of self-regulated learning compared to higher levels.

5. Discussion

This study aimed to develop a classification model for online social support and further reveal the relationship between social support and learning burnout as well as the potential moderating role of self-regulated learning in this association. This section will discuss the key findings of the study, provide insights for researchers and educators in distance learning, and propose future research directions.

5.1. Automatic content detection of social support using machine learning

A discussion forum is a crucial place where online learners can exchange social support with each other. Given the enormous number of posts generated by a large number of learners, it becomes challenging for instructors to manually analyze social support and provide targeted interventions. This research aims to achieve automatic and effective content detection of social support in online forums using machine learning techniques. Based on the performance comparison between specific traditional machine learning models and deep learning, this study found that BERT-Bi-LSTM outperformed BERT and other models. This is consistent with the research of Cai et al. (2020), which demonstrated that BERT-Bi-LSTM outperforms both BERT and Bi-LSTM in predicting the sentiment orientation of Internet users. Furthermore, the analysis results validated the powerful pre-training ability and sequence modeling capability of BERT-Bi-LSTM, even with small, imbalanced datasets (Li et al., 2022a). In the BERT-Bi-LSTM model, BERT can provide rich semantic representations, while Bi-LSTM aids in capturing long-term dependency relationships within sequences. This combination enables a more comprehensive capture of semantic and sequential features in textual information (Si & Wei, 2023). Moreover, the results indicated a strong synergy between the diverse contexts captured by the recursive modeling of Bi-LSTM and the global modeling of BERT (Cornegruta et al., 2016).

In addition, it can be observed that the BERT-Bi-LSTM model exhibits higher consistency with human-annotated data compared to other models, based on Cohen's Kappa values. Thus, we believe that the BERT-Bi-LSTM model can automatically process and classify large volumes of social support textual data, thereby reducing labor costs and subjective biases. This is supported by the research of Singh and Jain (2024), which suggested that the combining BERT with BiLSTM addressed the issue of overlooking long-range dependencies in textual data. To validate the applicability of the model in real learning scenarios, we manually analyzed the correctness of the BERT-Bi-LSTM model classification based on the coding rules. The results indicated that the BERT-Bi-LSTM model, trained using datasets from the diverse courses, could be extended to other courses, even though the data were unbalanced (i.e., emotionally supportive posts constitute a small percentage of all posts). These results provide insights into the application of effective and robust models in both educational practice and research. However, it is important to emphasize that the primary objective of this study is the automated analysis of social support content, rather than the preprocessing stage. To improve the model's applicability in specific educational contexts, future research should focus on developing an automated system for detecting the relevance of posts.

5.2. The relationship between social support and learning burnout

According to the results analyzed by multiple regression modeling, the number of social support entries, encompassing both informational and emotional support received in discussion forums, exhibited negative correlations with the three dimensions of learning burnout. In general, the research results further validated previous research findings, demonstrating that learners are prone to experience learning-related exhaustion as a consequence of insufficient social support (Barratt & Duran, 2021). Regarding the role of various forms of social support in learning burnout, it was suggested that learners who received more informational support in discussion forums tend to suffer less from emotional exhaustion and improper behavior. The findings supported the assertion that the more resources individuals obtain, the less emotionally exhausted they become. This can be explained by the substantial role of informational support in alleviating learners' stress, anxiety, and depression in the context of online education (Jin & Hahm, 2021). Furthermore, we contend that the informational support learners receive could stimulate the emotional effects of social support, such as feeling attention, understanding, and encouragement. These, in turn, could trigger positive psychological states among online learners, helping to reduce anxiety and emotional exhaustion. This is supported by the research of Jia et al. (2020), which indicated that informational support from teachers can stimulate positive emotions in learners, thereby enhancing student engagement.

In addition, the results emphasized the significance of informational resources in guiding learners' behaviors during online learning. This aligns with the findings of Xing et al. (2018), highlighting that informational exchange among members of online communities facilitates their active participation. Essentially, informational support can be considered a behavioral response, and peer-to-peer knowledge support can help maintain the learning community socially and emotionally connected (Lloyd-Jones, 2021). From the perspective of internal cognition, informational support might encompass cognitive processes such as goal setting, planning, and implementation, which may assist students in regulating their learning behaviors. This form of informational support, referred to as self-efficacy-oriented message support in the research by Park et al. (2020), plays a significant role in fostering self-regulation. Nevertheless, the significant relationship between informational support and the low sense of achievement was not explored. One possible reason is that informational support primarily provides guidance or advice on specific issues and tasks in online forums, which tends to have a limited impact on deeper, more intrinsic aspects of achievement. In other words, while informational support helps individuals address immediate problems and accomplish particular tasks, it may not directly influence their overall sense of achievement, which also requires timely feedback on students' progress (Kulakow, 2020).

Additionally, the findings suggested that learners who obtained more emotional support were more likely to experience reduced emotional exhaustion and decreased sense of achievement. In previous research, emotional support obtained via social interaction has been identified as a necessary condition for establishing a sense of community commitment, personal responsibility, and satisfaction in online learning (Hernández-Sellés et al., 2019). According to the research findings, we found that when peers express their closeness and understanding regarding the problems faced by the learner receiving social support, it enhances the emotional connection between learners, thereby alleviating emotional exhaustion (Yu et al., 2024). Applying the Job Demands-Resources Theory (Bakker & Demerouti, 2007), it can be inferred that emotional resources from both peers and instructors directly affect learners' emotional responses. Conversely, the fulfillment of learners' emotional needs contributes to reduced emotional exhaustion. In addition, emotional support typically involves substantial understanding and encouragement from peers, which can help learners to build stronger social bonds and identities with others (Molinillo et al., 2020). More importantly, based on the self-determination theory, the positive feedback and encouragement provided through emotional support can enhance learners' competence (Ryan & Deci, 2022). As a result, students are more likely to believe that they are capable of overcoming academic challenges, thus boosting their sense of achievement. However, this study did not examine the significant role of emotional support in reducing learners' improper behavior, possibly due to the general nature of emotional support and individual differences in responsiveness to such support. Emotional support typically involves encouragement and validation on an emotional level (Shen et al., 2024), which may not provide adequate guidance or strategies for addressing specific academic challenges. Additionally, learners' self-regulation abilities play a significant role in shaping their learning behaviors (Lai et al., 2024). For those who lack effective self-regulation strategies or have high levels of self-regulation, relying solely on emotional support to manage their learning process may be insufficient.

5.3. The moderating role of self-regulated learning

This study further examined how learners' internal characteristics, particularly their levels of self-regulated learning, moderate the association between social support and online learning burnout. As shown by the results, levels of self-regulated learning moderate the negative impact of informational support on improper behavior, as well as the relationship between emotional support and emotional exhaustion. Both moderations indicate that the higher the level of self-regulated learning, the weaker the negative effect. The findings are consistent with the research of Lin et al. (2018), which delved into the moderating effect of self-regulated learning on the association between social support and attitudes towards web-based continuing learning. According to the Conservation of Resources Theory, individuals with higher levels of self-regulated learning are better equipped to effectively utilize and manage received support, thereby minimizing resource depletion associated with information processing (Tabor et al., 2020). In other words, when learners are less able to self-regulate their learning, goal setting, time management, and strategy adjustment need to be coordinated with external support (Chou & Zou, 2020). Informational and emotional support enable learners who are less able to self-regulate their learning to receive suggestions, encouragement, and trust from others, and to gradually reduce their learning burnout.

Specifically, for learners with lower levels of self-regulated learning, there was a negative correlation between the reception of informational support and improper behavior. This is supported by the notion that learners tend to rely on peer support due to self-regulation problems (Räisänen et al., 2021). Insights and advice from peers can assist learners in more effectively regulating the learning process, enabling them to control improper learning behaviors. However, it is noteworthy that there is no significant effect of informational support on improper behavior for learners with higher self-regulated learning. We can speculate that learners with high levels of self-regulation usually have a greater ability to deal with learning difficulties independently (Esnaashari et al., 2023), and the informational support received may be of low instructional value for their learning. Learners with higher levels of self-regulated learning may rely less on external informational support due to their unique learning abilities and motivational characteristics. In addition, the findings indicated that emotional support reduces emotional exhaustion more effectively in learners with lower self-regulated learning than in those with higher self-regulated learning. This supports previous research, indicating that learners with poor self-regulation skills may encounter limitations in external support, and are more susceptible to emotional exhaustion (Räisänen et al., 2020). Moreover, for learners with low levels of self-regulation, sufficient emotional support may increase their self-regulation during online learning. Therefore, it can be argued that online forums offer the capacity and mechanisms to support online learning, enabling each learner to benefit from the various social supports presented in the discussion forum posts (Li et al., 2022c). This, in turn, facilitates potential behavioral and emotional regulation through engagement in discussions. Furthermore, these findings align with social cognitive theory, which highlights that the environments individuals encounter are not determined at random; rather, they are frequently shaped by individuals through their actions (Schunk & DiBenedetto, 2020).

5.4. Theoretical and practical implications

These findings hold significant theoretical and practical implications. Firstly, existing research on social support and online discussion forums often depends on conventional social science methods, such as surveys, interviews, and content analysis. This study demonstrates that social support posts can be automatically identified with exceptional accuracy using deep learning models such as BERT-Bi-LSTM. The BERT-Bi-LSTM model trained in this study provides significant insights for enhancing the effectiveness of LLMs in text classification for online discussion forums, especially those based on the Transformer architecture. Although LLMs share underlying technical principles with traditional deep learning models, their classification results are usually more generic rather than context-specific. In future research, we look forward to applying more robust LLMs for social support categorization in online course forums. In addition, the current study advances our understanding of the impact of receiving social support in discussion forums on students' learning burnout. Specifically, the findings reveal that emotional support, such as encouragement and empathy from peers or teachers, helps alleviate emotional exhaustion and improper behavior. Meanwhile, informational support, like guidance on learning strategies, contributes to positive emotional responses and fosters a sense of achievement. Furthermore, the study highlights that individual learners actively regulate their emotional, behavioral and cognitive responses through the exchange of social support, fostering sustained engagement within online learning environments. Furthermore, we explored internal factors, such as self-regulated learning, as a moderator of the association between social support and student burnout, highlighting the significance of both social and cognitive factors in online learning burnout.

In practice, the understanding of various types of social support in online discussion forums and their correlation with learning burnout is essential for educators and course designers, as it enables a reconsideration of the assessment criteria for online learning experiences, especially regarding the advantages of social support exchange within discussion forums. To facilitate the provision and reception of social support in online discussion forums, developers of online course platforms, such as MOOCs, should integrate automated post-detection components based on BERT-Bi-LSTM to identify various types of social support. An additional issue to address is the impact of LLMs on discussion forum interactions. Specifically, when LLMs are employed to generate content in forums, they can provide and receive various types of social support for learners, thereby altering the nature of online discussion forum interaction. Embedding LLMs based on high-quality BERT-Bi-LSTM models into forums to classify and generate specific social support could enhance the sustainable development of online interactions. Furthermore, establishing connections between multiple online courses is feasible, enabling various data from these courses to be effectively utilized for model training. Understanding the social support categories in online learning forums may help online instructors or course designers provide more tailored support to learners, and further alleviate student burnout. For example, instructors or peers should extend increased emotional support to learners experiencing a diminished sense of achievement. In light of the findings of moderation analysis, instructors must pay attention to the augmentation of students' self-regulated learning. Additionally, instructors should place greater emphasis on the behaviors of students with lower levels of self-regulated learning in seeking and receiving social support, since they need more social support to fill gaps in self-regulation compared to other learners. However, it is noteworthy that when applying the trained model to fields significantly different from the educational domain, such as finance, its effectiveness should be carefully considered due to fundamental differences in knowledge bases. Integrating social support texts from various fields or employing LLM-augmented data to construct more universally applicable models in future work will be beneficial for educators.

6. Conclusions

This study developed a deep learning model to classify social support in online discussion forums, explored the relationships between social support and online learning burnout, and investigated the moderating role of self-regulated learning in these relationships. First, the BERT-Bi-LSTM models demonstrated outstanding performance in accurately classifying social support texts in discussion forums. Second, regression analysis revealed various relationships between informational and emotional support and three dimensions of online learning burnout. Specifically, informational support negatively affected the dimensions of learning burnout such as improper behavior and a low sense of achievement, while emotional support was effective in alleviating emotional exhaustion and a low sense of achievement. Additionally, self-regulated learning moderated the relationships between informational support and improper behavior, as well as emotional support and emotional exhaustion. These findings underscore the importance of considering different types of social support and levels of self-regulated learning when designing online social interaction activities to prevent and mitigate student burnout in online learning environments.

However, several limitations should be addressed in future research. First, the discipline focus and data sample size of this study present some constraints. The use of convenience sampling from a single online course with small, unbalanced datasets may limit the generalization of the findings, as the sample may not represent the broader population of online learners. Further research could employ more diverse sampling methods, such as random or stratified sampling, to enhance the external validity and generalization of the results. Second, the broad categories of social support into informational and emotional types could be further refined. For instance, informational support could be broken down into specific subcategories such as advice and referral. Similarly, emotional support could include aspects like relationships, or expressions of caring. Exploring these more detailed subcategories of social support is an interesting and valuable area for exploration, though it falls beyond the scope of this study. Future studies could use machine learning models to classify these detailed subcategories and investigate their specific relationships with learning burnout, offering deeper insights into the mechanisms of social support affecting learning burnout. Moreover, both the quantity and quality of posts can be considered in measuring social support. While our current BERT-Bi-LSTM model significantly advances automated social support classification, there remains potential to further streamline the annotation process. Future work could explore integrating active learning techniques and large language models to enhance annotation efficiency while maintaining high reliability. Another limitation is the potential impact of anonymity on social support. While partial anonymity may encourage open communication and honest self-disclosure, it could also hinder trust and deeper interpersonal connections (Smedley & Coulson, 2021). Future studies should examine how varying levels of anonymity influence the reception and provision of social support.

CRediT authorship contribution statement

Changqin Huang: Writing – original draft, Supervision, Methodology. **Yaxin Tu:** Writing – review & editing, Writing – original draft, Methodology. **Qiyun Wang:** Writing – review & editing, Methodology, Conceptualization. **Mingxi Li:** Supervision, Methodology. **Tao He:** Formal analysis, Conceptualization. **Di Zhang:** Methodology, Formal analysis.

Data statement

Data and code used in our research are available at https://github.com/GitHubLink66/IESource.git.

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Data availability

Data will be made available on request.

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