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VIRTUAL CLASSROOM: COMPUTER SELF- EFFICACY AND LEARNING BURNOUT IN ASYNCHRONOUS E-LEARNING

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Abstract: Many ELT students in asynchronous e-learning may experience burnout despite having adequate technological skills. Understanding how computer self-efficacy (CSE) relates to burnout is therefore essential to support their well-being. The study aimed to investigate the correlation between CSE and learning burnout and to examine whether CSE predicts burnout among ELT students in an Open and Distance Learning (ODL) university. Using a correlational–predictive design, data from 38 students were analyzed through Pearson correlation and simple linear regression. Results showed varied CSE levels: basic computer skills ranked highest, followed by media-related skills, while web-based skills were lowest. Students appeared more confident with basic

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functions than with online or media tools. Exhaustion emerged as the strongest burnout symptom. A significant positive correlation was found between CSE and learning burnout (r = 0.370, p = 0.022), and regression analysis showed that CSE significantly predicted burnout (F = 5.709, p = 0.022), accounting for 13.7% of the variance. Each unit increase in CSE corresponded to a 0.480-unit rise in burnout. These results challenge the assumption that higher technological competence always reduces burnout. Instead, students with stronger CSE may over-engage with digital tools, increasing exhaustion. The findings highlight the need for balanced technology use and thoughtful e-learning design to protect students' well-being.

Keywords: *Asynchronous e-learning, computer self-efficacy, learning burnout, open and distance learning*

INTRODUCTION

E-learning, a technology-based learning approach, is fundamentally supported by LMS platforms. These systems organize, manage, and deliver e-learning courses. The concept of e-learning emerged alongside the widespread adoption of the internet and personal computers in the 20th century (Bezhovski & Poorani, 2016). As a critical component of e-learning, LMS facilitates the electronic delivery of educational materials to students over vast distances via the internet (Udin T et.al, 2022). According to Maltz and DeBlois, (2005), Arkorful Valentina and Abaidoo Nelly (2014), e-learning encompasses distributed learning, online distance learning, and hybrid learning models. E-learning processes involve technological infrastructure, digital platforms, content, and participants. Pedagogically, e-learning fosters deeper learner engagement with course material. It is characterized by two primary perspectives: technological and pedagogical (Devedzic, 2006, as cited by Bezhovski & Poorani, 2016).This method allows for flexible remote learning through features such as multimedia content, interactive quizzes, discussion forums, and communication tools.

In higher education, the adoption of learning management systems (LMS) has become increasingly widespread. LMS platforms, such as Blackboard, Moodle, and WebCT, are widely utilized virtual learning environments that integrate teaching and learning technologies across global higher education institutions (Annamalai et al., 2021). These platforms are designed to support pedagogical activities within a digital environment through web-based systems. Technological advancements enable students and teachers to share learning materials, manage tasks, and communicate online. Core LMS functions include course registration, participant statistics, scheduling, assessments, examinations, grading, synchronous and asynchronous communication, interactive applications, and audio/video file integration to enhance the teaching and learning process (Lonn & Teasley, 2009). LMS platforms offer flexibility, engagement, and convenience, allowing learning to occur anytime and anywhere (Kant et al., 2021). Open and Distance Learning (ODL) institutions have widely adopted LMS platforms to optimize educational practices and actively engage students in online learning.

Consequently, asynchronous e-learning has gained prominence in modern education. For over two decades, higher education institutions have incorporated asynchronous online courses into their curricula (Abuhassna et al., 2020). This learning mode allows students to learn at their own pace, offering scheduling flexibility and fostering self-directed learning. In asynchronous environments, students have access to audio/video lectures, handouts, publications, and presentations at their convenience (Perveen, 2016). This model encourages autonomy and critical engagement with learning materials. Amiti (2020) notes that asynchronous learning prompts critical thinking and reflective responses, as immediate reactions are not required. However, this learning mode demands that students independently manage their learning and actively participate in coursework

Despite its advantages, asynchronous e-learning presents challenges in sustaining student motivation and participation. The absence of face-to-face communication cues, such as tone, facial expressions, and body language, may hinder effective interaction and cause misunderstandings (Cartagena, 2023). Khotimah (2020) highlights that the lack of social interaction in asynchronous learning can lead to feelings of isolation and frustration. Additionally, technical issues, limited internet access, inadequate educational technology skills, and inflexible instructional materials exacerbate these challenges (Abdul & Maharida, 2022). Such obstacles can result in learning burnout, negatively impacting academic performance. Furthermore, Tomaszek and Muchacka-Cymerman (2024) categorize distance learning challenges into five areas: self-regulation, technological literacy, student isolation, technological adequacy, and system complexity. These categories highlight that both individual learner traits (such as self-regulation and technological literacy) and systemic/infrastructural factors (technological adequacy and system complexity) jointly influence the success of distance learning. In particular, student isolation can exacerbate burnout and reduce learning engagement, especially when learners lack sufficient self-regulation skills to proactively manage their study rhythm and technology usage. Therefore, a comprehensive strategy is required to address the complex issues of asynchronous e-learning. Educational institutions must prioritize the development of student self-regulation skills, invest in digital infrastructure, and provide dynamic and adaptable learning materials. Furthermore, creating meaningful interactions between students and tutors - through forums, video feedback, or online meetings can effectively mitigate the obstacles.

As a result of these challenge is learning burnout which refers to the fatigue and disengagement students experience during academic tasks, characterized by reduced motivation, social withdrawal, and diminished achievement (Huang et al., 2023). Novianti (2021) explains that academic burnout stems from stress and psychological strain during the learning process, manifesting as exhaustion, cynicism, and reduced professional efficacy. While online learning can inspire academic success through active participation and engagement (Sur et. al., 2020), factors such as personality traits and learning conditions contribute to burnout. (Weng et al., 2015) assert that insufficient engagement in technology-supported environments increases burnout risk. Although digital tools promote adaptability, they may also hinder social and emotional development in students lacking digital self-efficacy. This condition may lead to a cycle of disengagement, where students feel overwhelmed by digital demands, resulting in increased stress and reduced academic satisfaction. As a result, computer self-efficacy is essential for mitigating the impacts of online learning settings. Students are more likely to participate actively, adjust to new platforms, and look for answers to technical problems if they have confidence in their technological skills.

Given this crucial role, it is essential to understand the concept of computer self-efficacy (CSE) and how it shapes students' experiences in online learning environments. CSE is critical for success in online learning. CSE is defined as an individual's confidence in performing computer-related tasks (Nurhikmah H, 2019). Karsten (2012) further describes CSE as self-perceived competence in general computing tasks. Students with high self-efficacy exhibit confidence in understanding lessons, solving problems, and tackling complex courses (Ahmad & Safaria 2013). These students adapt well to e-learning due to their technological skills and intrinsic motivation. Sidhiq A, Majorsy U and Rini Q.K. (2023) found that self-efficacy and user experience significantly influence student satisfaction with e- learning. Udin et. al. (2022) also highlights the importance of self- efficacy in enhancing student comfort and self-awareness during online learning. However, while these studies have primarily examined CSE in relation to student satisfaction and performance, limited research has investigated how computer self-efficacy may influence learning burnout, particularly in asynchronous e-learning environments where learners must manage higher autonomy and technological demands. Murphy et al. (1989) identify three CSE components: beginner, advanced, and mainframe computer skills, which collectively assess students' technological competence and task performance. These categories reflect the progressive development of computer-related abilities, from basic operational skills such as file management and word processing to more complex functions involving software integration, networking, and system administration. Thus, it is necessary to include psychological belief, practical skill, and technological competence as interconnected aspects of computer self-efficacy that together affect students' performance in online learning settings. Technological competence refers to the ability to successfully adjust to and navigate a variety of digital platforms; psychological belief represents students' confidence in their ability to use technology; and practical skill relates to their ability to carry out computer-related tasks. By combining these components promotes student engagement, reduces academic burnout, and raises satisfaction.

Grounded in Bandura's (1986) Social Cognitive Theory, this study assumes that individuals' beliefs in their capabilities influence how they approach challenges and regulate their emotional responses in learning tasks. In online education, CSE represents this confidence within technology-mediated environments. Although previous studies have explored CSE in relation to student satisfaction and performance (Sidhiq, Majorsy & Rini, 2023; Udin et al., 2022), limited attention has been given to its connection with learning burnout, particularly in asynchronous e-learning where students must independently manage technological demands and self-regulation. Therefore, this study aims to close this gap by examining how CSE predicts learning burnout, thereby contributing to a better understanding of students' psychological adaptation in virtual classrooms.

This is especially relevant in Open and Distance Learning (ODL), where the LMS plays a central role in instructional delivery. It functions as the main platform which students interact with peers and instructors, access learning resources, and turn in assignments. High level of computer self-efficacy is expected as an aspect to mitigate learning burnout. At *Universitas Terbuka*, English Language Teaching (ELT) students rely on e-learning to manage academic activities effectively. The study investigated the correlation between learning burnout and CSE in the context of asynchronous e-learning and found out the predictive power of CSE on learning burnout among ELT students at an ODL university. This study specifically integrated computer self-efficacy and burnout in online learning to examine the influence of confidence on academic and emotional resilience. Additionally, it provided context-specific insights relevant to *Universitas Terbuka*, where asynchronous learning is predominant, and it offers recommendation to improve students' well-being and academic success.

METHOD

Approach and Design

The study employed a quantitative approach utilizing two primary statistical methods. Pearson Product Moment correlation analysis was used to examine the correlation between learning burnout and computer self-efficacy (CSE) variables. Additionally, Simple Linear Regression analysis was applied to investigate the influence of CSE on learning burnout. Before conducting these analyses, the researchers verified that the data met the necessary assumptions through normality testing using the Kolmogorov–Smirnov test and linearity testing. The methodological approach is defined as a correlational-predictive research design, where the researchers first identified the relationship between variables and then determined the predictive impact of CSE on learning burnout.

Participants

The study involved 38 undergraduate ELT students from *Universitas Terbuka* (UT) Pontianak, Indonesia. Participants were selected using a simple random sampling technique from a population of 73 students. This method ensures that each population member had an equal chance of being selected. Similarly, Noor et al. (2022) describe that this selection method provides every individual an equal opportunity to take part in the study.

Instruments

Two main instruments were used in this study. First, CSE questionnaire was developed by Teo et al. (2010). It consists of 12 items assessing students' CSE in three domains — basic, media-based, and web-based skills. Second instrument is Maslach Burnout Inventory–Student Survey (MBI-SS) adopted from Maslach and Jackson (1982), containing 15 items categorized into exhaustion, cynicism, and professional efficacy (Maharani, 2022).

The CSE instrument captures participants' confidence and technological skills, while the MBI measures the well-being consequences potentially influenced by that confidence. To better align with the e-learning context, several MBI items were slightly modified to include phrases such as "e-learning." For example, the item *"I feel emotionally drained by my studies in e-learning"* was used to ensure responses reflected the online learning experience.

Data Collection and Analysis

Following data collection through the two questionnaires, the researcher conducted descriptive and inferential analyses to answer the research questions. Descriptive statistics (mean and standard deviation) were calculated to describe the central tendency and dispersion of the data. The Pearson Product Moment correlation was used to determine the relationship between CSE and learning burnout, while Simple Linear Regression analysis examined the predictive influence of CSE on learning burnout. Normality was tested using the Kolmogorov–Smirnov test, and linearity was verified through ANOVA-based linearity testing. These procedures ensured that the data met statistical assumptions before hypothesis testing. Regression results were interpreted based on the R-value, R^2, and standard error of the estimate to understand the direction, strength, and predictive power of CSE toward learning burnout. The research adhered to the ethical standards of *Universitas Terbuka*. Participation was voluntary, and informed consent was obtained from all respondents before data collection. Participants were assured that their responses would remain confidential and used solely for academic research purposes.

FINDINGS

The Level of Computer Self-Efficacy

Computer self-efficacy involves three indicators namely basic computer skills, media-related skills, and web-based skills. These indicators contribute to an individual's confidence and capacity to proficiently employ technology in education. The researchers utilize the coefficient of variation (CV) to determine whether the standard deviation is low, moderate, or high. The formula of Coefficient of Variation (CV) = (Standard Deviation / Mean) × 100%. The coefficient of variation is particularly beneficial as it expresses the standard deviation as a percentage of the mean, allowing for easy comparison of variability across different data scales. Table 1 describes the coefficient of variation categories.

Table 1
Category of Coefficient of Variation (CV) By Gomes in (Vaz et al., 2017)

Category	CV Range
Low	CV < 10%
Moderate	CV 10-20%
High	CV > 20%
Very High	CV > 30%

After analyzing the data, the finding shows the level of CSE among ELT students across three skills domains: basic computer skills, media-related skills, and web-based skills—utilizing the mean, standard deviation, and coefficient of variation (CV). Table 2 describes the data analysis.

Table 2

Level of students' computer self-efficacy (CSE)

Statistics				
		Basic Computer Skills	Media-Related Skills	Web-Based Skills
N	Valid	38	38	38
	Missing	0	0	0
Mean		15.97	9.97	8.21
Std. Deviation		2.319	2.199	1.339
Coefficient of Variation (CV)		14.52	22.06	16.31

Table 2 shows that basic computer skills exhibit the highest mean score of 15.97 accompanied by a standard deviation of 2.319. This domain represents moderate coefficient of variation at 14.52%. This suggests that students' have similar levels of basic computer proficiency which relatively consistent self-efficacy levels among students for basic computing tasks. Meanwhile the media-related skills reveal a moderate mean score of 9.97 with a standard deviation of 2.199. Notably, the highest coefficient of the variation is 22.06%. This indicates that individuals exhibit significant variability in media-related skills, with some probably having strong skills and others having less, resulting in a larger skill gap. In contrast, the web-based skills record the lowest mean score of 8.21 accompanied by a standard deviation of 1.339. The coefficient of variation is 16.31%, reflecting a moderate variability of respondents' self-efficacy regarding students' web-based skills. Although students exhibit high confidence in basic computer skills, their confidence in web-based skills remains comparatively low. Consequently, enhancing computer self-efficacy is essential in online learning settings.

The Correlation between Computer Self-Efficacy and Learning Burnout

The normality test is used to determine whether two variables have a normal distribution. The following table demonstrates that both learning burnout (p = 0.088) and CSE (p = 0.167) had Asymp. Sig. (2-tailed) values that are higher than the significance level of 0.05, indicating that the data are normally distributed. As a result, it can be said that both variables have a normal distribution. As shown in Table 3, the obtained significance values ($p > 0.05$) indicate that both variables are normally distributed, allowing the use of Pearson correlation and regression analyses in subsequent procedures.

Table 3
Normality test

One-Sample Kolmogorov-Smirnov Test			
		Burnout	CSE
N		38	38
Normal Parametersa,b	Mean	43.79	34.16
	Std.Deviation	6.187	4.773
Most Extreme Differences	Absolute	.133	.122
	Positive	.133	.122
	Negative	-.104	-.098
Test Statistic		.133	.122
Asymp. Sig. (2-tailed)		.088c	.167c
a. Test distribution is Normal.			
b. Calculated from data.			
c. Lilliefors Significance Correction.			

Table 4 presents the results of the ANOVA test for linearity between CSE and learning burnout. The objective of the test is to ascertain whether the two variables have a substantial linear connection. The ANOVA table indicates that the linearity component is statistically significant, with F = 5.881 and p = 0.024, which is less than the significance level of 0.05. It indicates that learning burnout and computer self-efficacy have a significant linear relationship.

Table 4
Linearity test between CSE and learning burnout

			Sum of Squares	df	Mean Square	F	Sig.
Burnout * CSE	Between Groups	(Combined)	691.116	15	46.074	1.398	.232
		Linearity	193.853	1	193.853	5.881	.024
		Deviation from Linearity	497.262	14	35.519	1.078	.425
	Within Groups		725.200	22	32.964		
	Total		1416.316	37			

Table 5 below displays the result of a Pearson Product Moment, which discovers the correlation between computer self-efficacy (CSE) and learning burnout. The correlation analysis indicates a statistically significant positive relationship between Burnout and Computer Self-Efficacy (CSE) with the R-value 0.370 > the r-table 0.320, and a significance score 0.022 < 0.05. Since the R-value (0.370) is greater than the critical r-table value (0.320) and the p-value (0.022) is less than 0.05, indicating that the result is statistically significant.

Table 5
Correlations between CSE and learning burnout

		Burnout	CSE
Burnout	Pearson Correlation	1	.370*
	Sig. (2-tailed)		.022
	N	38	38
CSE	Pearson Correlation	.370*	1
	Sig. (2-tailed)	.022	
	N	38	38

*. Correlation is significant at the 0.05 level (2-tailed).

The Influence of Computer Self-Efficacy on Learning Burnout in Asynchronous E-Learning

Table 6
Level of learning burnout

		Exhaustion	Cynicism	Reduction of Professional Efficacy
N	Valid	38	38	38
	Missing	0	0	0
Mean		13.50	12.50	17.79
Std. Deviation		3.261	2.063	3.129
Coefficient of Variation (CV)		24.15	16.50	17.58

Table 6 presents statistical data on burnout measurements across three domains: exhaustion, cynicism, and reduction of professional efficacy including sample size, mean values, standard deviations, and coefficients of variation. The coefficient of variation (CV) for exhaustion is 24.15%, with a mean score of 13.50 and a standard deviation of 3.261. This relatively high CV indicates that there is significant variation in participants' levels of exhaustion, with certain individuals experience considerably higher or lower levels of exhaustion than others. Furthermore, the cynicism exhibits a mean score of 12.50 accompanied by a standard deviation of 2.063 and a CV of 16.50%. This suggests that students have a moderate level of cynicism and that their experiences of disengagement from their studies are relatively comparable. This pattern indicates that feelings of indifference or distancing from academic work are common across the sample, while not consistent. The consistent cynicism scores in relation to exhaustion may indicate common academic experiences or environmental factors affecting students' attitudes toward education.

The mean score of reduction of professional efficacy is 17.79, with a standard deviation of 3.129, and providing in a coefficient of variation of 17.58%. Similar to cynicism, this represents moderate variability, suggesting that feelings that perceptions of diminished professional efficacy fluctuate with some consistency among the students. The table reveals that exhaustion has the greatest relative variability among the three burnout domains, while cynicism and reduction of professional efficacy show moderate levels of variation. This suggests that experiences of exhaustion may be more personalized, or situation-dependent compared to the other burnout domains in this sample. Table 7 provides a summary of the regression model used to examine the relationship between CSE and learning burnout.

Table 7
Model summary of the relationship between CSE and learning burnout

Mode l	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.370a	.137	.113	5.827
a. Predictors: (Constant), CSE				

The correlation coefficient (R), the coefficient of determination (R Square), the adjusted R Square, and the standard error of the estimate are among the important statistical data presented in the table. The predictor (CSE) and learning burnout have a moderately positive relationship, as indicated by the R value of 0.370. The R Square value of 0.137 shows that CSE explains about 13.7% of the variation in learning burnout. This means CSE influences learning burnout to a certain part, however other factors also contribute. The Adjusted R Square, which corrects for the number of variables in the model, lowers this estimate slightly to 11.3%. This provides a clear representation of CSE's contribution in Learning Burnout.

Correlation and regression analysis were carried out to determine how CSE and learning burnout relate to one another in asynchronous e-learning environments. The objective of these analyses was to find out whether students' burnout experiences during online learning were significantly impacted by their confidence in computer technology. The details of these results are presented and discussed below.

Table 8
The relation between CSE and learning burnout in asynchronous e-learning environments

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	193.853	1	193.853	5.709	.022b
	Residual	1222.462	36	33.957		
	Total	1416.316	37			
a. Dependent Variable: Burnout						
b. Predictors: (Constant), CSE						

The ANOVA table indicates that learning burnout is significantly impacted by CSE in asynchronous e-learning. The F-value is 5.709 with a significance level (p-value) of 0.022, which is less than 0.05. The result is statistically significant indicating that CSE can serve as a predictor of learning burnout. In other words, the degree of burnout that students encounter when learning online is correlated with their level of computer confidence.

The following table describes the regression analysis's findings, which investigates the impact of CSE on learning burnout. Table 9 includes standard errors, and unstandardized coefficients (B)and the standardized coefficients (Beta) for both the constant and CSE.

Table 9
The regression analysis of the impact of CSE on learning burnout

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	27.410	6.920		3.961	.000
	CSE	.480	.201	.370	2.389	.022
a. Dependent Variable: Burnout						

Based on the statistical analysis presented in Table 9, CSE demonstrates a positive relationship with learning burnout. Specifically, the regression coefficient of 0.480 indicates that for each single unit rise in CSE, learning burnout correspondingly increases by 0.480 units. In addition, CSE has a moderate impact on learning burnout, as indicated by the standardized coefficient (Beta) of 0.370. CSE has a t-value of 2.389 and a p-value of 0.022, both of which are below 0.05. These metrics confirm that the observed relationship between CSE and learning burnout is statistically significant, meaning CSE is an important factor in predicting learning burnout.

Surprisingly, the coefficients analysis above suggests that students with higher CSE may encounter increased degrees of learning burnout during asynchronous e-learning activities. It is described from Positive Regression Coefficient (B = 0.480) signifies that a one-unit increase in CSE leads to a rise of 0.480 units in learning burnout. This study contradicts prior beliefs suggesting that elevated computer self-efficacy is generally associated to reduce learning burnout. A reason for this inconsistency may be that students with greater technological skills are frequently expected to undertake more complex digital tasks leading to screen fatigue. Furthermore, students with higher CSE may encounter pressure to undertake more complex technology tasks in online learning. These aspects need more investigation in future studies.

DISCUSSION

The Level of Computer Self-Efficacy among ELT Students

The findings indicate that ELT students in UT Pontianak demonstrate different levels of computer self-efficacy across three different domains. Students' confidence in basic computer skills is the highest (mean = 15.97, CV = 14.52%), suggesting that their skill in basic computing activities varies moderately and is generally constant. This aligns with the findings of Saidi and Arefian (2022), who discovered that students who have a higher level of computer self-efficacy are more confident while using online learning resources and effectively managing digital learning settings. As a result of the growing incorporation of technology into everyday academic activities, the moderate coefficient of variance indicates that the majority of students have comparable levels of basic computer competency.

On the other hand, students showed moderate variability (CV = 16.31%) with a much lower mean score in web-based skills (8.21). This finding is particularly important due to the function of web-based apps in asynchronous e-learning environments. Students who lack confidence in their web-based skills may find it difficult to use online learning environments efficiently, which could lead to dissatisfaction and burnout. This is consistent with research by Cancino and Towle (2022), who found a strong correlation between perceptions of fully online language learning components and computer self-efficacy. The findings imply that students with lower internet proficiency may hold more negative perceptions of online learning.

Students' abilities to use different media forms for learning varied significantly, as seen by the highest variability in media-related skills (CV = 22.06%). Students with poorer media-related self-efficacy may struggle to engage with multimedia content, which leads to gaps in the learning process. Higher computer self-efficacy is associated with lower levels of burnout (Hartono & Prapunoto, 2024), indicating that the wide range of media-related skills could explain differences in burnout experiences among students.

The Correlation between Computer Self-Efficacy and Learning Burnout

According to the statistical analyses carried out, the results of this study show a significant positive correlation between students' learning burnout and CSE. The normality test indicates that burnout ($p = 0.088$) and CSE ($p = 0.167$) both have normal distributions. Additionally, the Pearson correlation coefficient ($r = 0.370$, $p = 0.022$) revealed a statistically significant positive relationship between computer self-efficacy and learning burnout. Furthermore, the linearity test showed a significant linear relationship between these variables ($F = 5.881$, $p = 0.024$). The findings align with previous research investigating the correlation between academic burnout and computer self-efficacy within educational settings. Cancino and Towle (2022) identified a strong correlation between students' opinions of totally online language learning components and their levels of computer self-efficacy. The research indicates that students with varying levels of computer self-efficacy encounter different experiences in online learning, which may have an impact on how likely they are to experience burnout.

According to Aria et al. (2024), the most significant element influencing students' academic burnout during online learning is technology infrastructure. This implies that if the technology infrastructure is inadequate or problematic, even students who have a high level of computer self-efficacy may become burned out. The frustration arising from technological limitations could potentially offset the protective benefits of high self-efficacy. Saidi and Arefian's (2022) research of Iranian high school students during COVID-19 lockdowns provides more information. They discovered that the majority of the students had moderate to low levels of computer self-efficacy. Students with high CSE viewed online learning as flexible and helpful for individualized learning, and they also showed higher confidence while utilizing online resources and managed it effectively. On the other hand, students with poor CSE reported higher levels of stress, more diversions, and difficulty using digital platforms.

These results highlight the complex connection between learning burnout and computer self-efficacy. Although having technological proficiency can help one navigate digital learning environments, it does not always prevent burnout and can even promote it in some situations. Therefore, educational institutions must consider about establishing technology focused treatments that not only improve students' technological proficiency but also offer methods for preserving psychological health in increasingly digitalized learning environments.

The Influence of Computer Self-Efficacy on Learning Burnout

The finding reveals an unexpected relationship between CSE and learning burnout in asynchronous e-learning environments. The statistical analysis shows that CSE explains about 13.7% of the variation in learning burnout, with a positive regression coefficient of 0.480. This means that for every unit increase in computer self-efficacy, learning burnout increases by 0.480 units. This finding contradicts conventional understanding of the relationship between technological competence and burnout. Typically, higher computer self-efficacy is expected to reduce learning burnout, as technically proficient students should navigate online learning platforms with greater ease and less frustration. However, the finding implies the opposite dynamic occurs in asynchronous e-learning settings. The contradiction appears most clearly in the positive direction of the correlation. While earlier research by Cancino and Towle (2022) revealed that higher computer self-efficacy correlates with more positive perceptions of online learning, this finding shows higher CSE is associated with increased burnout. This challenges the assumption that technical competence serves as a protective factor against negative learning experiences.

Several factors might explain this contradictory finding. First, students with higher computer skills may experience greater expectations in digital environments. Instructors might assign them more complex technological tasks, assuming their proficiency will make these assignments manageable. This increased workload could contribute to exhaustion over time. Second, technically proficient students may spend more time engaged with digital platforms due to their comfort with technology. Without the structure of synchronous learning, these students might struggle to establish boundaries between academic work and personal time. As Samudra and Matulessy (2021) noted, extended online learning engagement significantly correlates with academic stress. The research found that technology infrastructure significantly impacts academic burnout, suggesting that even skilled technology users are susceptible to digital fatigue.

The burnout dimensions in this study showed varied patterns, with exhaustion demonstrating the highest variability (CV=24.15%). This suggests that energy depletion varies considerably among participants, potentially influenced by different patterns of engagement with digital learning platforms. Students with higher CSE may experience more exhaustion despite their technical competence because they engage more intensively with digital learning tools. The practical implications of the findings suggest that educational institutions should develop targeted support strategies for technically proficient students in asynchronous e-learning environments. These might include guidance on establishing healthy technology boundaries, clear expectations regarding digital tasks, and structured opportunities for non-digital academic engagement.

While this study highlights the role of computer self-efficacy in influencing burnout, it is important to recognize that it interacts with other psychological and contextual factors. As noted earlier, elements such as self-regulation, motivation, and technology infrastructure (Aria et al., 2024) also play significant roles in shaping students' experiences in online learning. Compared with these factors, computer self-efficacy primarily addresses the confidence dimension of learners' interaction with technology, whereas self-regulation relates to time management and persistence, and motivation governs emotional engagement. Understanding how these factors collectively influence burnout provides a more holistic view of student well-being in asynchronous virtual classrooms.

Implications for Asynchronous E-Learning Practice

The findings present several implications for e-learning practice. First, flexible support tools should be provided due to the different levels of computer self-efficacy. Meanwhile, students with lower self-efficacy may need more guidance and help. Second the positive correlation between computer self-efficacy and learning burnout highlights the need for balanced technology integration in e-learning environments. While technological proficiency is valuable, excessive reliance on digital tools may contribute to burnout even among technically skilled students. Instructors and instructional designers should consider incorporating regular "digital breaks" and varied learning activities that reduce continuous screen exposure. Lastly, several students in low computer skills who encounter difficulty with online learning platforms should get training and support educational institutions and instructors to get more comfortable within asynchronous e-learning. This is particularly crucial given that Aria et al. (2024) identified technology infrastructure as the most significant factor influencing academic burnout. Finally, the moderate coefficient of determination (R^2 = 0.137) suggests that addressing computer self-efficacy alone will not eliminate learning burnout. Comprehensive approaches that also target other potential contributors to burnout—such as workload management, social connection, and intrinsic motivation—are essential for creating sustainable e-learning environments.

Based on these findings, several concrete recommendations can be made for instructors and curriculum designers in asynchronous ELT settings. First, integrating short digital literacy workshops at the beginning of each semester can help equalize students' confidence levels across basic, media, and web-based skills. Second, instructors should design activities that alternate between online and offline components, for example, encouraging students to draft assignments offline before uploading them, to reduce screen fatigue. Third, implementing structured peer-support forums can help students with lower computer self-efficacy seek help without feeling isolated. Finally, curriculum designers should ensure that LMS interfaces remain intuitive and that technical tasks align with students' current proficiency levels to prevent overexertion among highly skilled students.

CONCLUSION

This study investigated the complex relationship between learning burnout and computer self-efficacy (CSE) in asynchronous e-learning settings among ELT students at *Universitas Terbuka*. The study focuses on CSE and burnout variables in asynchronous e-learning without concerns on external factors such as internet connectivity. The analysis indicated that CSE domains were at different levels. Basic computer skills had the highest average score and moderate variability followed by media-related skills which consider the greatest variability, and web-based skills with the lowest mean score. Compared to web-based and media-related skills, students showed more confidence in basic computer skills. In correlation analysis, the Pearson correlation coefficient revealed a statistically significant positive relationship between CSE and learning burnout, while the linearity test showed a significant linear relationship between these variables. However, in simple linear regression reveals an unexpected relationship between CSE and learning burnout in asynchronous e-learning. The statistical analysis shows that CSE explains about 13.7% of the variation in learning burnout, with a positive regression coefficient of 0.480. This indicates that for each unit increase in CSE, learning burnout rises by 0.480 units. Contrary to common expectations that higher computer skills would alleviate learning burnout by enabling smoother navigation of online platforms with reduced frustration, However, the finding implies the opposite dynamic occurs in asynchronous e-learning settings.

In conclusion, computer self-efficacy does not consistently mitigate burnout. In certain situations, it may increase burnout by encouraging greater utilization of digital platforms. These findings highlight the need for approaches to technology integration in e-learning environments that balance technical proficiency development to mitigate digital fatigue and maintain students' well-being. Future research might explore to longitudinal studies that monitor changes in burnout and computer self-efficacy over the academic term. Examining potential mediating factors such as digital overload, technostress, or perfectionistic tendencies among technically proficient students would also deepen the comprehension of this relationship.

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DECLARATION OF AI AND AI-ASSISTED TECHNOLOGIES

During the preparation of this manuscript, Chat-GPT and Jenni AI were used exclusively for optimizing language clarity and readability through proofreading purposes. The authors have reviewed and edited the content carefully to ensure its accuracy and quality and take full responsibility for the content of the publication after the use of these tools.

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