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Profiles of e-learners based on learning motivation: differences in peer-to-peer confirmation and mental health

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Introduction: Previous research employing latent profile analysis has considerably advanced our understanding of student motivation in online learning environments. However, a gap remains in exploring how mental health and social dimensions—specifically anxiety, depression, and peer-to-peer confirmation—influence these motivational profiles. Although prior studies indicate associations between student learning motivation, mental health, and peer-to-peer confirmation, their role in motivation profile is less understood. The current study aims to explore motivational profiles of e-learners, their differences in mental health, and their links to peer-to-peer confirmation.

Methods: A cross-sectional survey of 595 university e-learners (33.3% male, 66.7% female; mean age 26.34 years, SD 8.4; age range 18–56) was conducted. Four instruments were used in this study: the Learning Motivating Factors Questionnaire, the Patient Health Questionnaire-9 (PHQ-9), the Generalized Anxiety Disorder Scale (GAD-7), and Student-to-Student Confirmation Scale. Latent profile analysis (LPA) identified motivation profiles. Binomial logistic regression tested whether peer-to-peer confirmation dimensions predicted profile membership, and independent-samples t-tests compared anxiety and depression between profiles.

Results: The latent profile analysis (LPA) identified high motivation profile and low motivation profile. The results of the binomial logistic regression revealed that peer-to-peer confirmation, namely, individual attention, was a significant predictor of student motivation: higher individual attention predicted high motivation profile membership, suggesting that personalized interactions between peers serve as a protective factor against low motivation. Additionally, e-learners in the low motivation profile had significantly higher levels of anxiety and depression.

Conclusion: This study contributes to the growing research on student motivation, peer-to-peer confirmation, and mental health in e-learning. The latent profile analysis underscored the importance of individual attention as a unique and powerful factor in motivating students in e-learning environments. As higher education continues to embrace e-learning models, it will be essential to integrate effective mechanisms for peer interactions and communication processes to enhance student motivation. Additionally, the findings revealed that e-learners in the low motivation profile had significantly higher levels of anxiety and depression, which suggests that students' mental health should be among the priorities of education policies targeting correlates of academic achievements. Future studies should examine factors that are both protective for e-learners mental health and beneficial for learning outcomes.

KEYWORDS

mental health, peer-to-peer confirmation, learning motivating factors, motivation, e-learning

1 Introduction

The process of transition from face to face to online environments, accelerated by the COVID-19 pandemic and recent technological advancements, has raised new challenges and requires technological, physical, and psychological readiness from the teachers and the learners (Zekaj, 2023). While e-learning offers flexibility, it might also bring psychological difficulties such as increased anxiety, depression (Cao et al., 2020; Wathelet et al., 2020; Rogowska et al., 2020; Elmer et al., 2020) and also introduce a set of motivational challenges (Gonzalez-Ramirez et al., 2021; Hicks et al., 2023).

Previous studies have shown that motivation plays a major role in students' engagement and academic outcomes (Ryan and Deci, 2000; Guay et al., 2000; Martin, 2023). Motivated students are more likely to actively engage in learning, leading to enhanced academic outcomes (Nguyen et al., 2023). High motivation typically results in increased interest, commitment, and diligence in completing learning tasks, ultimately improving academic performance (Radović et al., 2022). Conversely, low motivation is associated with a lack of enthusiasm toward learning and passive engagement in educational activities, often leading to poorer academic performance (Mauliya et al., 2020). Students with high intrinsic motivation exhibit lower levels of anxiety and depression and demonstrate greater engagement with their learning (Azila-Gbettor et al., 2021).

Recent studies use latent profile analysis (LPA) to better understand how student motivation manifests in e-learning. For example, Wang et al. (2025) used a multilevel LPA to identify student and institution levels profiles of motivation and engagement, highlighting the importance of institutional climate for learning and satisfaction. Zhao and Ling (2022) explored how self-management and self-monitoring strategies relate to motivation, engagement, and wellbeing among university students, identifying three distinct profiles that were associated with wellbeing and autonomous motivation. Focusing on language learning, Li and Zheng (2018) found that profiles with high self-efficacy and task value, and low task anxiety, were linked to better outcomes in a one-to-one computing environment. These findings suggest that e-learning approaches should be tailored to learners' diverse motivational profiles.

Xu (2022) integrated achievement goal theory and expectancy-value theory, identifying four online assignment motivation profiles that differed in self-regulation behaviors, such as distraction management, time organization, motivation monitoring, and emotion regulation. The findings suggest that targeted interventions tailored to specific motivational profiles may improve student engagement and performance in online assignments. Similarly, Vanslambrouck et al. (2019) explored self-regulated learning (SRL) in blended education and identified learner profiles that varied from autonomous to externally regulated; these differences were predicted by motivational values. Achievement motivation predicted profile membership. Although De Vincenzo and Carpi (2024) did not focus explicitly on online learning, they found that university students' motivational profiles differed in academic performance, engagement. The three subgroups showed differences in academic outcomes, such as GPA, dropout intention, psychological outcomes, with the more intrinsically motivated profile being more self-regulated and reporting higher grades, lower dropout intention, higher self-efficacy, and lower psychological distress.

While prior latent profile studies (Wang et al., 2025; Zhao and Ling, 2022; De Vincenzo and Carpi, 2024; Li and Zheng, 2018; Vanslambrouck et al., 2019) explained motivation via LPA in learning context, but there's still a gap in understanding motivational profiles within e-learning by anxiety and depression and peer-to-peer confirmation. Furthermore, the differences between motivational profiles in mental health outcomes, such as anxiety and depression have yet to be thoroughly explored (Cao et al., 2020; Elmer et al., 2020). Research has shown that students' motivation varies significantly based on individual profiles (Guay et al., 2000). Identifying these motivational profiles in e-learning contexts can reveal how they relate to mental health outcomes.

Furthermore, peer-to-peer confirmation has been recognized as an important peer interaction construct (Kerimoğlu et al., 2023) and communicative process (Johnson and LaBelle, 2016, 2024) in educational settings. Kerimoğlu et al. (2023) explain, that "confirmation exists in a classroom when a student's response to the course content is acknowledged by fellow students, when assistance is supplied, or when a student receives individual attention from other student." While peer interaction has been studied in traditional classroom settings (Sato, 2021), the impact of peer-to-peer validation in virtual, e-learning platforms remains under-researched.

The current study aims to fill these gaps by exploring latent motivational profiles among e-learners and examining how these profiles are related to mental health outcomes and peer-to-peer confirmation.

2 Literature review and hypotheses development

2.1 Learning motivation and its role in e-learning

Understanding student motivation in e-learning requires a multidimensional approach by psychological theories. Pekrun (2006) Control-Value Theory of Achievement Emotions posits that students' academic emotions are shaped by their perceived control over learning activities and the subjective value they assign to them: when learners perceive high control and value, they are more likely to experience positive emotions. Studies show that academic emotions are significantly related to students' motivation, learning strategies, cognitive resources, self-regulation, and academic achievement, as well as to personality and classroom antecedents (Pekrun et al., 2002). Goal-Setting Theory (Locke and Latham, 1991, 2002) suggests that challenging and attainable goals enhance motivation and performance. Research shows that in e-learning goal-setting is especially important (Schunk et al., 2008; Schunk and Zimmerman, 2008).

Some theories explain motivation based on a neurobiological perspective (Kringelbach and Berridge, 2016), psychological cycles (Deckers, 2013), or human goals and needs, such as Maslow's hierarchy of needs, Herzberg's two-factor theory, Alderfer's ERG theory, and Self-Determination Theory (SDT) (Ryan and Deci, 2000, 2022). SDT, which is one of the most comprehensive motivation theories, focuses on the role of intrinsic and extrinsic motivation and identifies the basic psychological needs that drive motivation: autonomy (sense of agency, control and independence), competence (feeling capable, confident and effective), and relatedness (feeling connected to others and social structures) (Ryan and Deci, 2000, 2022). Prior research revealed that learners can enhance the satisfaction of the need for autonomy by having control over the timing, methods, and content of their learning, the need for competence—by the successful completion of tasks, and the need for relatedness—by social connections with peers, both in-person and online (Chen et al., 2010). Any reduction in these elements is expected to have a detrimental effect on learners' motivation, involvement, and academic success (Chiu, 2023). So, motivation plays a critical role in shaping learning behaviors and academic success (Ryan and Deci, 2000; Schunk and Zimmerman, 2008), with motivational factors influencing both the engagement and persistence of students (Law et al., 2010).

Both intrinsic and extrinsic forms of motivation play a crucial role in learners' levels of engagement and academic performance (Jones, 2013). Cerasoli et al. (2014) highlights that intrinsic and extrinsic motivations frequently coexist and interact in complex ways, making it important to consider both types of motivation. In programming e-learning, intrinsic motivation is driven by curiosity about coding and the sense of accomplishment gained from completing programming tasks (Boguslawski et al., 2025), whereas extrinsic motivation stems from external influences such as deadlines, evaluations, or the prospect of career advancement (Boguslawski et al., 2025).

Research suggests that intrinsic motivation positively correlates with achievement motivation (Steinmayr et al., 2019) and typically leads to greater engagement and improved performance (Vansteenkiste et al., 2004). Numerous studies have consistently demonstrated that intrinsic motivation plays a significant role in academic performance and student engagement (Ngo et al., 2021; Liu et al., 2024). For example, Taylor et al. (2014) found that intrinsic motivation remained a critical factor in predicting high academic achievement even when initial levels of academic success were accounted for. Froiland and Worrell (2016) found that intrinsic motivation not only predicted better academic outcomes but also facilitated sustained student engagement across various demographics. Moreover, it was demonstrated that intrinsic motivation is closely related to self-efficacy, locus of control, and personal interests, all of which foster a deeper commitment to learning activities, and that students who learn online have a greater degree of autonomy in managing their educational experiences (Susanti et al., 2023). This was also supported by Guay et al. (2000) who revealed that self-regulation and independent learning leads to success. Nevertheless, it was also found that extrinsic motivation can be useful in encouraging students to stay on task and meet deadlines, but it can interfere with intrinsic motivation (Ryan and Deci, 2000). For example, rewards may lead to a temporary boost in motivation for some students, but they may also diminish intrinsic motivation for others (Hewett and Conway, 2015).

2.1.1 Learning motivating factors in e-learning

E-learning requires a higher degree of self-motivation and independence (Wong et al., 2021). Based on Vroom's (1964) expectancy theory and the works of Harackiewicz et al. (1997, 1998, 2002) and Law et al. (2010) proposed a framework categorizing motivational factors into distinct domains that play a crucial role in student engagement: intrinsic (individual attitude and expectation and challenging goals) and extrinsic (clear direction (perceptions of clear and structured learning objectives and regular feedback to boost motivation), reward and recognition, punishment, social pressure and competition) motivation. Research revealed that when students understand their goals and the path to success, they are more likely to engage and perform better (Hendry et al., 2006). Motevalli et al. (2020, p. 68) wrote that "students are motivated when they have goals" and suggested that "it is important students have learning goals instead of performance-oriented goals," advocating learning for one's self-interest or self-improvement. They find that interest in learning for personal growth leads to long-term engagement. Punishment can have negative effects, leading to anxiety, fear of failure, and disengagement (Ryan and Deci, 2000; Skinner, 1969). While positive competition can stimulate motivation, excessive focus on comparison can hinder intrinsic motivation (DiMenichi and Tricomi, 2015). Law et al. (2010) underscore the importance of fostering peer-learning environments that encourage collaboration and support over unhealthy competition. Thus, Law et al. (2010) offered a comprehensive framework for conceptualizing motivational factors, which is applied in this study. Hartnett (2016) and Barak (2010) have noted that while various studies have attempted to explore e-learning motivation, the findings are ambiguous, suggesting a need for more focused research in this area. Moreover, the persistence of students in programming e-learning has been insufficiently studied (Ngo et al., 2021), despite some successful attempts by Boguslawski et al. (2025) to identify thematic categories that impact learning: bespoke learning, affect and support.

2.2 E-learning and mental health challenges

Previous studies revealed that motivated students are more likely to employ strategies such as effective stress or time management that safeguard their mental health (Schunk and Zimmerman, 2008). Conversely, a lack of motivation is associated with procrastination or poor academic performance, which contribute to psychological distress (Barak, 2010). Prior research also revealed higher levels of anxiety, depression, and fatigue among students engaged in online learning environments (Wathelet et al., 2020; Acoba, 2024; Cao et al., 2020; Bolatov et al., 2020). During the pandemic up to 38% of students experienced moderate to mild levels of depression, anxiety, and stress, with a significant portion of students reporting severe anxiety (Jiang et al., 2021), and over half of the students met the diagnostic criteria for generalized anxiety disorder (52%) and depression (63%) (Aslan et al., 2020). The mental health consequences of the pandemic have been particularly severe for students, with global increases in stress and anxiety disorders (Zarowski et al., 2024). More severe manifestations of anxiety and depression are correlated with a marked decrease in e-learning motivation, or even its complete absence (Akour et al., 2020), despite mild or high anxiety has been associated with an increase in motivation (Al Majali, 2020). These findings highlight the urgent need for continuous monitoring of students' mental health, as the psychological consequences of the pandemic are likely to persist well-beyond the immediate crisis (Rutkowska et al., 2021, 2022).

Yaghi (2021) found that students experience higher levels of stress in e-learning and reported poorer mental health outcomes, including increased anxiety, depression, and overall psychological distress. Cognitive overload and frustration with problem-solving are prevalent stressors (Robins et al., 2003). Research suggests that anxiety levels can be significantly related to the coping strategies employed (Budimir et al., 2021), while depression levels are often contingent upon the availability of social support (Acoba, 2024). Social distance can exacerbate feelings of worthlessness, heightening worry, anxiety, and fatigue (Brooks et al., 2020), Conversely, social support, which included peer-to-peer confirmation, was linked to better mental health (LaBelle and Johnson, 2021) but the links between these constructs needs further exploration.

2.3 Peer-to-peer confirmation in e-learning

Central to a student-centered approach (Hoidn and Reusser, 2020; McCombs and Whisler, 1997) is the concept of peer-to-peer confirmation. Johnson and LaBelle (2016) define peer-to-peer confirmation as a "transactional process by which students communicate that they endorse, recognize, and acknowledge their peers as valuable and significant individuals," and this impact student engagement, both in-class and outside the classroom, contributing to deeper involvement in academic discussions and group study sessions.

According to Self-Determination Theory (SDT), social factors such as positive peer feedback are instrumental in shaping students' intrinsic motivation and their sense of competence (Ryan and Deci, 2000, 2022). When students perceive that their efforts are acknowledged and appreciated by their peers, they are more likely to feel competent and motivated to persist with their learning tasks. In contrast, the lack of such peer recognition can result in feelings of isolation, diminished self-esteem, and a decline in motivation (Rovai, 2002). Peer-to-peer confirmation concept is also aligned with social identity theory, which posits that individuals derive a sense of self-worth and identity from the groups to which they belong (Tajfel and Turner, 1986). In the context of e-learning, receiving positive reinforcement from peers can strengthen students' sense of belonging to the learning community, thereby mitigating feelings of alienation and stress (Edwards and Hardie, 2024). Peer-to-peer confirmation is crucial in remote learning environments, fostering opportunities for students to interact, enhancing the overall learning experience (Kerimoğlu et al., 2023) and reducing mental health challenges, as it buffers the negative psychological effects of stress and anxiety, especially in high-pressure academic settings (Johnson and LaBelle, 2024; LaBelle and Johnson, 2021). Positive feedback from peers improves not only motivation but also emotional belonging (Baumeister and Leary, 1995); it helps "students' find their fit in the university environment and feel that their fears and anxieties are normal rather than the exception" (Kelly, 2024), as students perceive their efforts as meaningful and appreciated by their peers (Pittman and Richmond, 2008). Johnson and LaBelle (2024) notes that "the communicative process by which students are made to feel valuable and significant as members of the classroom, student-to-student confirmation comprises three factors (i.e., individual attention, acknowledgment, and assistance) that have been associated with a myriad of positive student outcomes" (Johnson and LaBelle, 2024). Despite numerous studies exploring the correlates of this construct, the links with students' mental health in e-learning environment, are still under-researched.

In summary, prior research has indicated that psychological challenges can negatively affect academic performance and motivation (Ryan and Deci, 2000), and students' motivation and peer-to-peer confirmation may presumably contribute to mental health (LaBelle and Johnson, 2021; Zhang et al., 2024). However, there is limited research on how students' different latent motivational profiles are related to mental health outcomes such as anxiety, and depression, particularly in e-learning. Therefore, this study intended to fill this knowledge gap and evaluate how motivational profiles relate to peer-to-peer confirmation and mental health. The purpose of this study is to identify latent motivational profiles based on students' learning motivation factors in e-learning education and to examine how these profiles are associated with mental health outcomes (anxiety, depression) and peer-to-peer confirmation. The following hypotheses were formulated: H1. Latent Profile Analysis will identify multiple, statistically distinct profiles of e-learning students, each characterized by a unique pattern of learning-motivation factors (e.g., varying combinations of intrinsic, extrinsic orientations), rather than a single homogeneous motivational profile. H2. Latent profile membership can be linked to peer-to-peer confirmation. H3. Latent profiles would differ in students' mental health parameters, including anxiety and depression.

3 Materials and methods

This research utilized a cross-sectional design to explore the latent profiles withing the e-learners sample and their links with peer-to-peer confirmation, and differences in mental health.

3.1 Sample

In the full sample of 749 participants, a total of 595 participants had no missing data. All analyses were conducted using a sample of 595 individuals. The study involved a total of 595 participants: 33.3% male participants ($n = 198$) and 66.7% female participants ($n = 397$). The mean age of the participants was 26.34 years (Median – 23, Mode 19, SD = 8.444, Skewness – 1.141), with ages ranging from 18 to 56 years. A participants studied e-learning in various Lithuanian Universities and Turing College courses. Participation in the study was voluntary, and the participants did not receive any compensation.

3.2 Instruments

To examine the variables of interest, four established instruments were utilized: the Learning Motivating Factors Questionnaire (Law et al., 2010), the Patient Health Questionnaire-9 (PHQ-9) (Kroenke et al., 2001), the Generalized Anxiety Disorder Scale (GAD-7) (Spitzer et al., 2006), and Student-to-Student Confirmation Scale (LaBelle and Johnson, 2018). The Lithuanian translations of these instruments were back-translated to ensure consistency with the original English versions.

3.2.1 Student-to-student confirmation

To measure peer-to-peer confirmation, we applied 25-items Student-to-Student Confirmation Scale, developed by LaBelle and Johnson (2018). The student-to-student confirmation scale measure learners perceptions of confirming behaviors from their fellows. In scale was three subscales: individual attention, acknowledgment, and assistance. 10-items measured individual attention (assess participants' reception of confirming messages which let them know that they are significant as unique individuals. e.g., "My classmates express interest in getting to know me outside of class"), 9-items measured acknowledgment (assess participants' experience receiving messages that acknowledge their abilities related to academics and course content.; e.g., "My classmates tell me that they are impressed by my abilities"), and 6-items measured assistance (assess participants' reception of confirmation from peers in the form of assistance or help; e.g., "My classmates are willing to help me study for tests"). Each item was measured using a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree. Validation studies confirmed the three-dimensional structure of the Student-to-Student Confirmation Scale, evidencing the instrument's internal consistency (LaBelle and Johnson, 2018). Cronbach's alpha for the scale in this study was 0.965.

3.2.2 The PHQ-9

The Patient Health Questionnaire-9 (PHQ-9) is a widely validated and commonly used instrument for assessing depressive symptoms (Kroenke et al., 2001). In recent years, it has been widely used in studies that explore how students feel during online learning. For example, Ionescu et al. (2023) found that students who reported more symptoms of depression using the PHQ-9 were less satisfied with their online learning experience. Dirzyte et al. (2021b) showed that higher depression scores were related to lower learning motivation during e-learning. Our study has explored how distinct motivational profiles—identified via latent profile analysis—relate to mental health among e-learners. These studies show that PHQ-9 is useful for understanding students' mental health in online learning. This is important, because students' mental health and motivation are often connected and can influence how they learn online.

The Patient Health Questionnaire-9 (PHQ-9) (Kroenke et al., 2001), which consists of 9-items, was employed to assess the severity of depression symptoms, such as loss of interest in activities and feelings of hopelessness. Participants rated each item on a 4-point scale, ranging from 0 (not at all) to 3 (nearly every day). The total score, which ranges from 0 to 27, was used to assess depression severity, with higher scores indicating more severe symptoms. Scores above 10 are considered indicative of a clinically significant level of depression. Previous research has validated the PHQ-9 as a reliable tool for measuring depression, with internal consistency reported at $\alpha = 0.87$ (Kroenke et al., 2001). Cronbach's alpha for the scale in this study was 0.888.

3.2.3 The GAD-7

The Generalized Anxiety Disorder Scale (GAD-7) (Spitzer et al., 2006) was used to assess generalized anxiety symptoms. The GAD-7 is a widely used, brief self-report instrument, one of the most reliable measures of generalized anxiety disorder for assessing various populations, including college students (Löwe et al., 2008; Bártolo et al., 2017; Ionescu et al., 2023), demonstrating excellent reliability (Cronbach's $\alpha > 0.85$) and construct validity. Its brevity and ease of administration makes it suitable for large-scale survey research, preserving methodological rigor while minimizing respondent burden. This 7-item self-report questionnaire asks participants to rate the frequency of symptoms such as nervousness, excessive worry, and restlessness, using a 4-point Likert scale, where 0 indicates "not at all" and 3 indicates "nearly every day." The total score ranges from 0 to 21, with higher scores indicating more severe anxiety symptoms. Scores above 10 are generally considered indicative of clinical anxiety levels. The GAD-7 has demonstrated strong reliability, with a reported internal consistency of $\alpha = 0.89$ (Spitzer et al., 2006). Cronbach's alpha for the scale in this study was 0.908.

3.2.4 The Learning Motivating Factors Questionnaire

The Learning Motivating Factors Questionnaire (Law et al., 2010) was used to assess intrinsic and extrinsic factors of students' motivation to learn. This 19-item instrument evaluates factors: individual attitude, challenging goals, clear direction, rewards and recognition, punishment, social pressure and competition. Each item is rated on a 6-point Likert scale from 1 (disagree very much) to 6 (agree very much). Cronbach's alpha for the scale in this study was 0.869.

3.3 Data collection procedure

The survey was administered online: https://www.psytest.online (last accessed on 23 November 2024), ensuring ease of access for participants and adherence to the ethical standards for data privacy. Participants were informed of the study by e-mail and voluntarily provided their consent to participate in the research (introductory email containing a brief description of the study: purpose, procedures, and potential risks was sent to each participant). Following informed consent, participants completed the instruments at their convenience, ensuring anonymity and confidentiality of their responses. The study received approval from the Institutional Review Board at Klaipeda University (Approval No. STIMC—BMTEK-P03, 12 April 2021).

3.4 Statistical analysis

For the data analysis, we used SPSS v29.0 (IBM Corp., Armonk, NY, USA) and Jamowi 2.6.26.0. In the preliminary analysis, the descriptive statistics were calculated, followed by Latent Profile Analysis (LPA), binominal regression, and independent samples' T-Test.

Numerous studies applied LPA (or LCA) to understand motivation, self-regulated learning, or engagement (Wang et al., 2025; Zhao and Ling, 2022; De Vincenzo and Carpi, 2024; Li and Zheng, 2018), but typically without PHQ-9 or other depression measures. LPA is a sophisticated statistical technique commonly used in psychological research to identify unobserved subgroups within a population by categorizing individuals into distinct profiles based on their responses to a set of observed variables. The Latent Profile Analysis (LPA) has become an increasingly popular method for identifying subgroups or "profiles" within heterogeneous populations, helping to investigate how multidimensional constructs cluster within individuals (Ferguson et al., 2020). Unlike traditional clustering methods such as k-means or hierarchical cluster analysis, which rely on heuristic algorithms and distance measures, LPA uses maximum likelihood estimation to probabilistically assign individuals to profiles, providing fit indices (e.g., AIC, BIC, entropy) to guide model selection and offering more objective, replicable classification (Nylund-Gibson and Choi, 2018). Compared to traditional cluster analysis, LPA offers statistical fit indices, handles measurement error, and provides a probabilistic framework for classification (Nylund-Gibson and Choi, 2018). This person-centered method is particularly suited for detecting heterogeneous motivational profiles in educational settings.

Previous studies have applied LPA to investigate motivational profiles and engagement patterns in educational contexts (Li and Zheng, 2018), yet integration with mental health measures such as the PHQ-9 remains scarce, particularly in e-learning settings. In this study, LPA was employed to identify latent motivational profiles from continuous input variables reflecting e-learning motivation. To investigate factors influencing latent profile membership, a binomial logistic regression analysis was applied using peer-to-peer confirmation as a predictor of profile membership. Additionally, independent samples *T*-Tests was applied to identify the differences in profiles based on mental health, namely, anxiety and depression. In this research, we considered p-values < 0.05 to be statistically significant. In line with recent literature, the study's overarching goal was to elucidate how latent subgroups differ in peer-to-peer confirmation, and mental health, providing empirical guidance for future research.

4 Results

Descriptive statistics (means, standard deviations, and correlations) of the learning motivating factors questionnaire subscales in this study are reported in Table 1.

The frequency of the self-reported depression categories in this sample are presented in Table 2.

The frequency of the self-reported anxiety categories in this sample are presented in Table 3.

Means, standard deviations, and correlations between the PHQ-9 and the GAD-7 scales in this study are reported in Table 4.

Descriptive statistics of the student-to-student confirmation questionnaire subscales in this study are reported in Table 5.

TABLE 2 The frequencies of the PHQ-9 self-reported categories.

PHQ-9	Frequency	Percent	*p*
Minimal depression (0–4)	208	34.96	<0.001
Mild depression (5–9)	186	31.26	<0.001
Moderate depression (10–14)	103	17.31	<0.001
Moderately severe depression (15–19)	62	10.42	<0.001
Severe depression (20–27)	36	6.05	<0.001

TABLE 3 The frequencies of the GAD-7 self-reported categories.

GAD-7	Frequency	Percent	*p*
Minimal anxiety (0–4)	256	43.03	<0.001
Mild anxiety (5–9)	198	33.28	<0.001
Moderate anxiety (10–14)	86	14.45	<0.001
Severe anxiety (15–21)	55	9.24	<0.001

TABLE 1 The Learning Motivating Factors Questionnaire: descriptive statistics and correlations between the subscales.

Learning motivation variables	M	SD	1	2	3	4	5
1. Individual attitude and expectation	4.72	0.83	–				
2. Challenging goals	4.41	1.06	0.406***	–			
3. Clear direction	4.99	0.78	0.673***	0.475**	–		
4. Reward and recognition	4.86	0.93	0.552***	0.125**	0.497**	–	
5. Punishment	3.38	1.33	0.259***	0.098*	0.245**	0.206**	–
6. Social pressure and competition	3.46	1.18	0.254***	0.247**	0.211**	0.236**	0.429**

M, mean; SD, standard deviation.
*$p < 0.01$; **$p < 0,01$; ***$p < 0.001$.

The LPA, which was applied to test H1 and examined how different patterns of motivational variables emerge among participants, suggested two classes: Model 6 yielded the lowest Bayesian Information Criterion (BIC) value (BIC = 9,253.10), indicating the best overall model fit. The BIC is a robust model comparison statistic that balances model complexity and goodness of fit, where lower values signify better fit. Additionally, other model comparison indices such as the Akaike Information Criterion (AIC = 9,012.00), Adjusted BIC (AWE = 9,768.00), and Consistent AIC (CAIC = 9,308.00) further supported the selection of Model 6 as the optimal model: these indices, while similar to BIC, adjust for the number of parameters in the model and sample size, ensuring a more precise evaluation of model fit. The LogLik (−4,451.00) metrics further supported an acceptable fit.

The two-profile model was selected based on multiple fit indices and theoretical interpretability. However, an entropy value of 0.529 suggests low to moderate classification accuracy and the distinction between profiles should be interpreted with caution, indicating some overlap between the classes but still allowing meaningful group differentiation. This limitation raises concerns about the precision of individual classification and the overall stability of the profile structure, a risk of misassignment (∼20%) and undermines the confidence in distinguishing between profiles. Therefore, the results should be viewed as preliminary, and further research is needed to validate these profiles using larger samples and alternative methods. This indicates that while there was some degree of overlap between the identified latent classes, there was still sufficient differentiation to meaningfully interpret the results. Low to moderate entropy values are commonly observed in LPA, and while higher values (closer to 1) are ideal, values around 0.60 are generally considered adequate for meaningful subgroup differentiation. Table 6 provides fit statistics for the selected two-class Model 6.

Table 6 presents fit indices for selected two-class latent profile models. Model 6 shows improved fit relative to earlier models, with the highest log-likelihood (−4,451) and the lowest AIC (9,012) and BIC (9,253) values, suggesting better model parsimony and fit. However, its entropy value (0.529) was lower than in previous models, indicating less clear class separation. Overall, Model 6 represents the best balance of fit indices among the compared two-class solutions, despite reduced classification certainty.

As summarized in Table 7, Class 1 exhibited higher mean scores on Individual Attitude and Expectation (5.12 vs. 3.91), Challenging Goals (4.73 vs. 3.76), Clear Direction (5.39 vs. 4.18), and Reward and Recognition (5.22 vs. 4.15). Class 2 generally reported lower motivational scores. Variances were the same for both classes on each variable, indicating parallel variability across classes. All differences between the classes were statistically significant ($p <$ 0.001), confirming that the two groups differ meaningfully in their motivational profiles.

On the whole, the LPA analysis revealed two distinct latent profiles. The first latent profile (Class 1, High Motivation Profile) is characterized by higher mean scores on most of the motivational variables, indicating a group of individuals with relatively high motivation. This profile represents 67.7 % of the total sample, n = 403. Individual Attitude and Expectation (M = 5.12, SE = 0.0472, $p <$ 0.001) was higher in this group, suggesting that these individuals hold strong, positive attitudes and expectations regarding their academic or learning experiences. Challenging Goals (M = 4.73, SE = 0.0582, $p <$ 0.001) also had a high mean, reflecting the participants in Class 1 are highly motivated by the pursuit of challenging goals. Clear Direction (M = 5.39, SE = 0.0391, $p <$ 0.001) was similarly elevated, suggesting that these individuals perceive a high degree of clarity regarding the direction of their tasks or goals. Reward and Recognition (M = 5.22, SE = 0.0490, $p <$ 0.001) showed that this group values rewards and recognition, which likely contributes to their higher motivation overall. Punishment (M = 3.63, SE = 0.0715, $p <$ 0.001) was the lowest of the variables, although it is still significant. This suggests that while the participants in Class 1 may respond to punishment, it is less of a motivating factor compared to rewards. Social Pressure and Competition (M = 3.69, SE = 0.0794, $p <$ 0.001) also scored relatively high, indicating that these individuals may be influenced by external pressures or competition in their environment. For this profile, the variances were relatively moderate across all variables, indicating a consistent pattern within the group, though some variability in responses does exist. For instance, Punishment (variance = 1.669) and Social Pressure and Competition (variance = 1.292) displayed relatively higher variability, suggesting that individuals in this group differ more in their responses to these specific motivational factors.

The second latent profile (Class 2, Low Motivation Profile) showed lower mean scores on most of the motivational variables compared to Class 1, reflecting a group of individuals with relatively lower motivation. This profile represents 32.3 % of the total sample, n = 192. Individual Attitude and Expectation (M = 3.91, SE = 0.0904, $p <$ 0.001) was notably lower in this profile,

TABLE 4 The PHQ-9 and the GAD-7: descriptive statistics and correlations between the scales.

Scales	M	SD	1
1. PHQ-9	6.4756	5.07990	–
2. GAD-7	8.0487	5.97210	0.556**

M, mean; SD, standard deviation. *$p <$ 0.05; **$p <$ 0.01.

TABLE 5 Student-to-student confirmation questionnaire: descriptive statistics and correlations between the subscales.

Student-to-student confirmation variables	M	SD	1	2	Skewness	Kurtosis
1. Individual attention	3.7279	0.78904	–		−0.606	0.919
2. Acknowledgment	3.2921	0.80634	0.645**	–	−0.451	1.021
3. Assistance	3.5555	0.82607	0.688**	0.546**	−0.594	0.805

M, mean; SD, standard deviation; *$p <$ 0.05; **$p <$ 0.01.

TABLE 6 LPA results: statistics for two-class models.

Model	LogLik	AIC	AWE	BIC	CAIC	CLC	KIC	SABIC	ICL	Entropy
1	−4,776	9,591	9,851	9,674	9,693	9,555	9,613	9,614	−9,756	0.798
2	−4,725	9,500	9,843	9,610	9,635	9,452	9,528	9,530	−9,719	0.745
3	−4,559	9,186	9,653	9,335	9,369	9,120	9,223	9,227	−9,444	0.717
6	−4,451	9,012	9,768	9,253	9,308	8,903	9,070	9,078	−9,464	0.529

TABLE 7 LPA results: means, standard errors, and variances across the classes.

Variable	Class 1 mean (SE)	Class 2 mean (SE)	Class 1 variance	Class 2 variance
Individual attitude & expectation	5.12 (0.05)	3.91 (0.09)	0.38	0.38
Challenging goals	4.73 (0.06)	3.76 (0.10)	0.93	0.93
Clear direction	5.39 (0.04)	4.18 (0.08)	0.3	0.3
Reward and recognition	5.22 (0.05)	4.15 (0.10)	0.63	0.63
Punishment	3.63 (0.07)	2.89 (0.09)	1.67	1.67
Social pressure & competition	3.69 (0.08)	3.00 (0.08)	1.29	1.29

indicating that these individuals have weaker expectations and attitudes toward their learning. Challenging Goals ($M = 3.76$, SE $= 0.0958$, $p < 0.001$) was also lower, suggesting these individuals are less motivated by challenging goals compared to those in Class 1. Clear Direction ($M = 4.18$, SE $= 0.0816$, $p < 0.001$) was lower but still notable, suggesting that individuals in Class 2 may have a moderate sense of clarity regarding their goals or tasks. Reward and Recognition ($M = 4.15$, SE $= 0.1034$, $p < 0.001$) was somewhat lower compared to Class 1, indicating that rewards and recognition are less motivating for this group. Punishment ($M = 2.89$, SE $= 0.0912$, $p < 0.001$) was significantly lower in Class 2, suggesting that punishment is a less significant factor for this group compared to Class 1. Social Pressure and Competition ($M = 3.00$, SE $= 0.0769$, $p < 0.001$) was similarly lower, indicating these individuals are less influenced by social pressures or competition. The variances in this group were similar to Class 1, with relatively high variances in Punishment (variance = 1.669) and Social Pressure and Competition (variance = 1.292). This suggests that while the average levels of these motivational factors are lower in Class 2, there is still considerable variation in how individuals in this profile respond to them. The line plot of the profiles is presented in Figure 1.

A plot showing the mean scores for each variable across the two latent profiles, allows for an easy comparison of how the profiles differ in terms of their motivational factors. Both latent profiles show a drop in punishment and social pressure and competition learning motivating factors, suggesting these are not effective motivators.

The analysis of both latent profiles (see Figure 1 in Section 4) shows that the patterns of estimates of the learning motivation factors in the graph are similarly distributed in both the high motivation profile and the low motivation profile. The highest estimates were in the first four learning motivation factors: individual attitude and expectation, challenging goals, clear direction, reward and recognition. Of these, the highest was clear direction, followed by reward and recognition. The lowest estimates were for punishment, social pressure, and competition. The second highest score was reward and recognition. This indicates that students should be rewarded and feel recognized during e-learning. The third most important factor in learning motivation was individual attitude and expectation, followed by challenging goals.

Following the identification of latent profiles, the study proceeded with regression analyses to test H2 and explore how peer-to-peer confirmation contributed to the identified classes. To assess the predictors of class membership, a binomial logistic regression model was conducted, using peer-to-peer confirmation factors, namely, Individual Attention, Acknowledgment, and Assistance as predictors. The omnibus likelihood ratio test ($\chi^2 = 5.33$, $p = 0.149$) indicated that these predictors, as a set, did not significantly improve the model fit beyond chance. However, Individual Attention emerged as a significant individual predictor ($p = 0.031$), suggesting that higher levels of Individual Attention decreased the odds of belonging to Class 2 (Odds Ratio = 0.63). The full regression results are presented in Table 3.

Table 8 presents the regression model assessing the predictive utility of Individual Attention, Acknowledgment, and Assistance for class membership. The intercept is not statistically significant ($p = 0.219$), with an odds ratio of 0.49, which indicates that the baseline odds of belonging to Class 2 (when all predictors are at zero) are relatively low. However, in this model, the coefficient for Individual Attention was 0.461, with a p-value of 0.031 ($p < 0.05$), indicating that an increase in Individual Attention decreased the likelihood of being classified in Class 2. The odds ratio (OR) of 0.63 with a 95% Confidence Interval (CI) of (0.41, 0.96) suggests that for every one-unit increase in Individual Attention, the odds of being classified in Class 2 (lower motivation) decrease by 37%. In practical terms, individuals who receive more Individual Attention are less likely to be in the lower motivation group (Class 2), indicating that Individual Attention is a protective factor against lower motivation. However, Acknowledgment and Assistance did not show statistically significant effects in predicting class membership in this model, indicating that these factors may

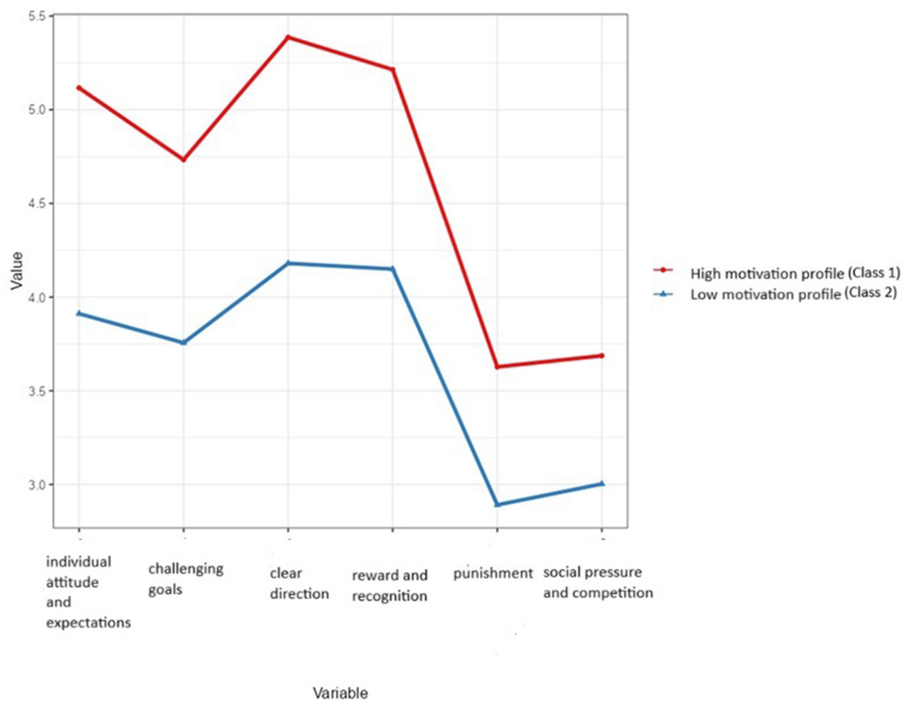

FIGURE 1
Latent profiles of e-learners, based on six learning motivating factors.

TABLE 8 Results of binominal regression.

Predictor	Estimate	SE	Z	p	Odds ratio	95% CI (lower, upper)
Intercept	−0.717	0.43	−1.23	0.219	0.49	(0.16, 1.53)
Individual attention	−0.461	0.21	−2.15	0.031*	0.63	(0.41, 0.96)
Acknowledgment	0.255	0.18	1.44	0.149	1.29	(0.91, 1.83)
Assistance	0.225	0.2	1.14	0.253	1.25	(0.85, 1.84)

*$p < 0.05$.

not play a central role in distinguishing between the latent profiles in this analysis.

Based on the results from the model fit measures, we can conclude that the current binomial logistic regression model does not show strong predictive power, AIC (Akaike Information Criterion) = 522 and BIC (Bayesian Information Criterion) = 539, $\chi^2 = 5.33$, with df = 3 and $p = 0.149$, McFadden's Pseudo $R^2 = 0.0103$. The low R^2McF suggests that the model only explains a small amount of variance in class membership. Individual attention ($\chi^2 = 4.71$, $p = 0.030$) showed statistical significance, indicating that one of the predictors in the model significantly improves the fit. Acknowledgment and Assistance showed non-significance (p-values of 0.145 and 0.250, respectively), meaning these predictors do not significantly contribute to the model's predictive power.

Thus, binominal regression showed that Individual Attention is the only statistically significant predictor ($p = 0.031$) in this model; as the odds ratio (0.631) indicates, higher levels of Individual Attention reduce the likelihood of belonging to Class 2 (lower motivation), suggesting that personalized attention can promote higher motivation. However, neither Acknowledgment nor Assistance predictor reached statistical significance ($p = 0.149$ and $p = 0.253$, respectively). Although Individual Attention emerged as a statistically significant predictor of class membership, the overall regression model did not reach significance, and the effect sizes were modest.

To test H3, which presumed mental health differences in different motivational profiles, Independent sample's T-test was performed. Table 9 presents the results of comparisons for Anxiety and Depression between groups (Class 1 and Class 2) based on the mean differences, effect size, and 95% confidence intervals.

Comparison of Class 1 (high motivation) and Class 2 (low motivation) on selected mental health variables showed that Class 2 exhibited significantly higher levels of anxiety ($p = 0.010$) and tended to report higher depression levels ($p = 0.05$) compared to Class 1.

Table 10 presents the descriptive statistics for Anxiety and Depression across two groups based on mean, median, standard deviation (SD), and standard error (SE). The mean of anxiety score for Class 2 is significantly higher than for Class 1, suggesting that Class 2 (the lower motivation group) has greater anxiety on average. The mean depression score for Class 2 is also higher than for Class 1, suggesting that Class 2 experiences more depression

TABLE 9 Independent samples *t*-test.

Mental health variables	Statistic	df	*p*	Mean difference	SE difference	Cohen's d	95% CI lower	95% CI upper
Anxiety	−2.584	416	0.01	−1.3985	0.5412	−0.2725	−0.4798	−0.0648
Depression	−1.944	416	0.05	−1.2442	0.6402	−0.2049	−0.4119	0.00232

on average. Similar to Anxiety, Class 2 shows greater variability in depression scores, as evidenced by a higher standard deviation and standard error. On the whole, these results suggest that Class 2 has significantly higher levels of both Anxiety and Depression compared to Class 1. The greater variability in these scores within Class 2 indicates a more diverse range of experiences within that group, with some members likely experiencing significantly higher levels of anxiety and depression than others.

TABLE 10 Descriptive statistics for anxiety and depression by Class 1 (high motivation profile) and Class 2 (low motivation profile).

Mental health variables	Class	N	Mean	Median	SD	SE
Anxiety	1	287	6.3	5	4.761	0.281
	2	131	7.69	6	5.869	0.5128
Depression	1	287	7.84	6	5.915	0.3492
	2	131	9.08	7	6.402	0.5593

5 Discussion

This study was among the first to explore e-learners' motivational profiles, their differences in mental health and links to peer-to-peer confirmation. The study's framework was built on several theoretical models in education: Learning motivation factors theory developed by Law et al. (2010), and Student-to-Student Confirmation model developed by LaBelle and Johnson (2018) and Johnson and LaBelle (2024). The study can also be linked to several theoretical frameworks: Self-Determination Theory (SDT) (Ryan and Deci, 2000, 2022), Pekrun's (2006) control-value theory, Goal-Setting Theory (Locke and Latham, 2002), Social Identity Theory (SIT) (Tajfel and Turner, 1986).

The aim of the research was to explore how latent profiles based on motivational factors could predict students' membership in specific motivational categories and identify mental health differences in these profiles. The profiles were primarily characterized by different patterns of motivational factors, including intrinsic and extrinsic. Students in the high motivation profile (67.7% of the sample) were highly engaged in their learning processes and were driven by both external recognition and intrinsic academic challenges. This aligns with Self-Determination Theory (Ryan and Deci, 2000), and Goal-Setting Theory (Locke and Latham, 2002), which suggest that individuals are highly intrinsically motivated in environments that provide clear goals, external validation, and challenges. According to these theories, high motivation is often fostered by a structured environment that provides both feedback and recognition. However, it is crucial to note that over-reliance on extrinsic motivators, such as rewards and recognition, could potentially diminish intrinsic interest over time, as suggested by Ryan and Deci (2000). Future research should explore whether this high level of motivation persists over time or whether it diminishes when external rewards become less salient or are removed.

The low motivation profile (32.3% of the sample) exhibited lower levels of all learning motivation factors. These e-learners demonstrated a more passive approach to learning: lower expectations and attitude, and a diminished response to rewards, recognition, social pressure, competition, or punishment. This suggests that students in the low motivation profile may lack confidence in their academic abilities or exhibit low levels of intrinsic motivation. These findings are consistent with Ryan and Deci (2000), who found that intrinsic motivation played a crucial role in fostering engagement, noting that it may struggle to meaningfully engage with learning tasks. Additionally, research by Motevalli et al. (2020) emphasized that students perform better when setting learning goals rather than performance-oriented goals. This supports our observation that high motivation e-learners benefit more from challenging goals and intrinsic drive, whereas low motivation e-learners may struggle without clear direction. As Schunk and Zimmerman (2008) suggested, disengaged learners who lack clear direction often require more advanced self-regulation strategies.

While rewards and recognition played a significant role to high-motivation e-learners, it is important to consider the implications of extrinsic rewards for motivation. These factors play a role in student dropout, as Dirzyte et al. (2023) found them to be statistically significant in predicting dropout odds for males, but not females Some studies, such as those by Cerasoli et al. (2014) and Hewett and Conway (2015), suggest that extrinsic rewards can be beneficial when they aligned with intrinsic motivation, especially when provided in an autonomy-supportive manner. In contrast, excessive focus on external rewards could undermine intrinsic motivation over time, which highlights the complexity of motivation in educational settings.

E-learners in the high motivation profile also have a high score of intrinsic motivation factors, including individual attitude and expectation, and challenging goals. These individuals demonstrated positive individual attitudes and high personal expectations regarding their academic success. Schunk et al. (2008) emphasize that students who maintain optimistic expectations about their abilities are more likely to persist in their efforts and succeed academically. Aligns with our findings, where high motivation students demonstrated resilience and a strong drive to achieve their academic goals and were driven by both intrinsic and extrinsic factors. Furthermore, Law et al. (2010) suggest that students motivated by challenging goals are more likely to engage in deeper learning and persist despite challenges. This concept is related with findings of Harackiewicz et al. (2002), who found that clear, ambitious goals can enhance motivation by providing well-defined targets that push students to expand their abilities. In the context of high motivation students, this aligns with Locke and Latham's (2002) goal-setting theory: challenging goals can enhance motivation and performance and encourage students to go out of their comfort zone, develop new skills, and strive for personal excellence.

In this study, punishment, social comparison, and competition—all recognized as extrinsic motivation factors—scored low across both high and low motivation profiles. Research suggests that structured learning objectives and regular feedback enhance student engagement, while excessive emphasis on punishment can lead to anxiety and disengagement (Ryan and Deci, 2000; Skinner, 1969). This finding aligns with previous research by Skinner (1969), who suggested that punishment may elicit short-term compliance but fails to foster long-term engagement. Our results suggest that e-learners in low motivation profile are not strongly motivated by external punitive measures. Their engagement appears more shaped by clear instructions and rewards, and recognition. However, even these positive external factors seem to have a limited impact, reinforcing the idea that low-motivation e-learners may struggle to find sufficient encouragement from either external rewards or clear learning direction (Schunk et al., 2008). Similarly, Schunk et al. (2008) emphasized that positive recognition reinforces students' sense of achievement, while our findings suggest that even external recognition has a diminished impact on low-motivation e-learners.

Interestingly, punishment received the lowest significant score among all the learning motivation factors. In this context, punishment refers to negative consequences such as reprimands, reduced grades, or other forms of discipline. This finding aligns with research indicating that intrinsic motivation and positive reinforcement more significantly impact students' academic outcomes (Ryan and Deci, 2000). Mahendra (2024) findings revealed that positive reinforcement significantly enhanced student motivation, whereas punishment affected it negatively. Law et al. (2010) concluded that punishment, as a motivator, is less effective than positive reinforcement for long-term motivation, often leading only to short-term compliance rather than fostering genuine interest or positive learning behaviors. For sustainable motivation, students need to feel autonomous and competent rather than coerced by negative consequences, as suggested by Ryan and Deci (2000) in their Self-determination theory.

The role of social pressure and competition in the low motivation profile shows the complexity of external motivators. Our findings, where these factors scored lower for less motivated e-learners, to contrast with Pekrun's (2006) control-value theory, which posits that negative emotions such as anxiety and shame can impair learning outcomes. Although some students may respond positively to competition, others may experience negative outcomes such as stress, anxiety, or disengagement. This dual effect is consistent with findings by Huguet et al. (1999), who noted that while some students are motivated by social comparison, others may suffer from performance anxiety. While positive competition can be beneficial, frequent comparisons may hinder intrinsic motivation. This aligns with the idea that social pressure and competition can increase motivation. Javaid et al. (2025) found that competition can enhance attention and memory, though individual differences and gender may moderate these effects. Law et al. (2010) explored how students are motivated by the desire to outperform peers in such environments. While social pressure and peer influence can increase motivation for some, others may feel anxious or demotivated by competition. Our study contributes to this perspective: social pressure and competition plays a more significant role in high motivation e-learners, while it has a lower score among e-learners in the low motivation profile.

This study evaluates how latent motivational profiles relate to peer-to-peer confirmation and mental health. The Student-to-Student Confirmation Theory (LaBelle and Johnson, 2018, 2020) posits that students benefit from direct, individualized interactions that make them feel valued and recognized within their learning environment. This aligns with our current findings.

Johnson and LaBelle (2024) identified three core components of student-to-student confirmation: individual attention, acknowledgment, and assistance. Our binominal logistic regression model show that individual attention was a significant predictor of membership in the high motivation profile, whereas acknowledgment and assistance were not significant predictors. We suggest that acknowledgment is less significant as an extrinsic factor than individual attention, possibly because of the role of social comparison. It could also be argued that assistance focuses more on cooperation but not as much on the sense of horizontal relationship; future research should explore this.

Our findings that individual attention in the e-learning environment plays a significant role in reducing the likelihood of e-learners membership in the low motivation group supports to the research on student engagement (Martin, 2023), Social Identity Theory (Tajfel and Turner, 1986), Self Determination Theory (Ryan and Deci, 2000, 2022), and motivation contexts (McCombs and Whisler, 1997; LaBelle and Johnson, 2018; Johnson and LaBelle, 2024). This also aligns with previous research that student-to-student confirmation enhance psychological wellbeing (LaBelle and Johnson, 2021). Rovai (2002) emphasized that students who received consistent peer confirmation reported greater integration into their learning community, which in turn reduced academic stress and disengagement. Dirzyte et al. (2021a) found that peer-to-peer confirmation, combined with positive automatic thoughts, was linked to increased flourishing in e-learning. Additionally, Kelly (2024) emphasized that personalized peer engagement could enhance students' confidence and intrinsic motivation to learn.

The current study also emphasizes the importance of peer-to-peer confirmation in mitigating negative psychological effects, such as depression and anxiety, in e-learning contexts. Existing literature suggests that peer interactions can reduce cognitive overload, enhance problem-solving skills, and alleviate stress (Robins et al., 2003; Yaghi, 2021). Moreover, peer engagement fosters a sense of belonging, reducing isolation-related anxiety and depression in online learning environments (Brooks et al., 2020; Budimir et al., 2021; Acoba, 2024). While individual attention emerged as a predictor of motivation, future research should further investigate the roles of acknowledgment and assistance in shaping learning experiences and their impact on mental health. However, further research is needed to explore the specific mechanisms through which peer-to-peer confirmation influences mental health outcomes.

Previous research emphasized that students' high motivation is linked to lower levels of stress, anxiety, and depression (Zhang et al., 2024). In contrast, low motivation in e-learning environments has been linked to increased psychological distress, as the lack of engagement and self-efficacy may exacerbate feelings of isolation and academic pressure (Yaghi, 2021; Pekrun, 2006). Dirzyte et al. (2021b) demonstrated significant associations between depression, anxiety, fatigue, and learning motivation in e-learning-based computer programming education.

Our findings indicate that e-learners in the low motivation profile experience higher levels of anxiety and depression, and individual attention to e-learners may reduce negative effects in mental health. The *T*-Tests of independent samples demonstrated that students in this group had significantly higher variable scores in anxiety and depression in comparison with their high-motivation peers. These findings relate to another research, such as Wang (2023), who emphasized the negative impact of distance learning on student mental health due to reduced social interaction and increased academic pressure.). Additionally, Walker et al. (2024) found that intrinsically motivated students tended to have higher academic performance and persistence rates, reinforcing the protective effects of motivation on mental wellbeing. Yusof and Johari (2023) demonstrated a strong correlation between motivation and mental health in post-pandemic learning environments, emphasizing that improved mental health fosters greater academic motivation. In summary, the findings suggest that students with lower academic motivation are at risk for anxiety and depression.

5.1 Implications for educational practices

The results suggest that interventions targeting motivation might benefit from being tailored to distinct learning motivation profiles. Law et al. (2010) proposed that understanding learning motivation factors allows educators to customize their teaching strategies to support various student types. For instance, individuals in high motivation profile may benefit from more clear directions and reward-based motivation strategies, strategies which emphasize goal-setting, reward systems, and clear guidance. Providing challenging tasks and recognizing achievements may serve to maintain or even increase student motivation (Ryan and Deci, 2000). On the other hand, individuals in the low motivation profile may require different approaches that foster intrinsic motivation and provide more clarity and direction. Educators could also consider reducing the reliance on punishment, focusing instead on encouraging students through positive reinforcement and clear, challenging goals. Since our research results showed that clear direction is the most important factor, followed by rewards and recognition, it is therefore crucial to consider and integrate these factors into e-learning process. Several ways are suggested below:

1. Using imagination to create a realistic image of oneself having received recognition (related to Rogers' theory of real and imagined self, Ismail and Tekke, 2023). This exercise would also strengthen students' self-confidence, especially after receiving awards and feeling recognized by both classmates and teachers. We believe that this is more related to the internal feeling of being recognized, while punishment is more related to a specific "place in line" in the peer group.
2. It is important to strengthen the sense of belonging for students in a learning group. This factor is related to the reward and recognition factor in teaching (the importance of a sense of belonging from A. Adler's individual psychology theory). Sense of belonging is also linked to peer-to-peer confirmation and can be strengthened by inviting students to cooperate in as many different tasks as possible, with various stages or levels. For example, a common task is to make a project which includes 3–5 stages, involving different participants and constant partners for project preparation. H2 results suggest that providing individual peer support can help boost student motivation, but other strategies may be needed to fully explain and enhance student engagement.
3. In the learning environment, it is crucial to consider interventions based on peer-to-peer confirmation while executing tasks. Prior research suggested that lack of direct peer engagement in online education can contribute to social isolation and reduced motivation (Rovai, 2002). Additionally, given that peer-to-peer confirmation has been linked to better mental health (LaBelle and Johnson, 2021), educators should prioritize student-centered approaches that foster one-on-one peer support interactions.
4. Our study results indicate that e-learners in low motivation profile report significantly higher levels of anxiety and depression, it consistent with previous research (Ionescu et al., 2023). We suggest that pedagogical strategies such as autonomy support, constructive feedback, and reduced cognitive load can enhance learning motivation for this students (Ryan and Deci, 2000; Pekrun et al., 2002). Educators should be trained how recognize anxiety and depression symptoms in online academic behaviors. They should respond with supportive, flexible strategies rather than punitive approaches. Peer communication processes can help buffer the effects of depression and anxiety (LaBelle and Johnson, 2021).

From an educational perspective, these results emphasize the need for structured peer engagement strategies, calling for tasks focused on direct and meaningful interactions between students and using the principle of peer-to-peer confirmation. Classroom interventions aimed at enhancing student motivation should consider peer mentoring programs, academic discussions with clear directions, and personalized individual attention in personal learning process. Peers could receive rewards and social recognition from classmates and teachers. Group work should be prioritized instead of individual tasks.

5.2 Limitations and future directions

This study has several limitations. The sample is overweighted toward women (66.7%). This could affect the results, future research should aim for a more balanced sample to better capture potential gender-specific effects. The two-profile solution ("high" and "low" motivation profiles) provides only a general level of differentiation. Although this classification was based on statistical fit and interpretability using LPA, more nuanced motivational profiles (e.g., intrinsic vs. extrinsic) could offer deeper insights.

Motivational profiles could be further detailed in future research to provide more comprehensive understanding. Its cross-sectional design limits the exploration of causal relationships. Longitudinal research is needed to examine motivational factors and their long-term effects on academic success. Next, this study used self-reported questionnaires to collect data and with the implied risk of individual subjectivity. Future research should integrate qualitative interviews or longitudinal methodologies to capture long-term peer interaction effects. Furthermore, as this study focuses on e-learning, its findings may not apply to traditional classroom settings. Replication studies in diverse educational contexts are necessary for validation. Additionally, a more diverse sample is necessary to determine the consistency of these findings across various cultural and educational contexts. The low McFadden's R^2 value (0.0103) indicates that the model explains only a small proportion of variance in motivation class membership. The low to moderate entropy (0.529) raises concerns of stability of the latent profile structure. Monte Carlo evidence suggests that values below 0.60 are associated with elevated misclassification rates (∼20%), warranting cautious interpretation. Future research should aim to refine profile indicators and expand the sample size to enhance classification reliability. Finally, other factors, such as teacher support, academic self-efficacy, may be stronger predictors of motivation, so future studies should incorporate additional psychological and contextual variables to improve predictive models.

6 Conclusion

This study contributes to the growing research on student motivation, peer-to-peer confirmation, and mental health in e-learning. The latent profile analysis identified high motivation and low motivation profiles, and underscored the importance of individual attention as a unique and powerful factor in motivating students in e-learning environments. As higher education continues to embrace e-learning models, it will be essential to integrate effective mechanisms for peer interactions and communication processes to enhance student motivation. Additionally, the findings revealed that e-learners in the low motivation profile had significantly higher levels of anxiety and depression, which suggests that students' mental health should be among the priorities of education policies targeting correlates of academic achievements.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Institutional Review Board of the Institute of Management and Psychology, based on the approval of the Biomedical Research Ethics Committee at Klaipeda University, No. STIMC—BMTEK-P03. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

RR-K: Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Methodology, Data curation, Conceptualization, Investigation. AD: Investigation, Data curation, Writing – review & editing, Methodology, Conceptualization, Writing – original draft, Visualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The author(s) declare that no Gen AI was used in the creation of this manuscript.

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