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Personality traits, anxiety, depression, and peer-to-peer confirmation as correlates of e-learning motivation

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Introduction: E-learning is a central component of higher education, yet maintaining student motivation remains difficult. Although personality traits, mental health, and peer support have each been linked to learning motivation, they are seldom examined simultaneously within an integrative framework. Drawing on Self-Determination Theory, this study examined the associations among personality traits, anxiety and depression, peer-to-peer confirmation, and learning motivating factors in e-learning.
Methods: A cross-sectional online survey was completed by 595 e-learners from Lithuanian universities and Turing College. Data were collected using an online self-report questionnaire. Participants completed the Learning Motivating Factors Questionnaire, the Patient Health Questionnaire-9 (PHQ-9), the Generalized Anxiety Disorder Scale (GAD-7), Student-to-Student Confirmation Scale, and Big Five Inventory-2 (BFI-2). Pearson correlational analyses and structural equation modeling (SEM) were used to estimate associations and indirect pathways.
Results: Extraversion, agreeableness, conscientiousness, and openness to experience showed positive correlations with e-learning motivation (r = 0.08–0.39, $p < 0.01$), whereas neuroticism and mental health symptoms were negatively correlated. The integrated SEM indicated acceptable fit: χ^2 (39) = 221, $p < 0.001$; CFI = 0.921; TLI = 0.888; RMSEA = 0.089 (90% CI [0.077, 0.100]), RMSEA $p < 0.001$, and SRMR = 0.075. The association between personality traits and e-learning motivation was primarily indirect via peer-to-peer confirmation (β = 0.062), whereas the indirect pathway via mental health was not significant. Peer-to-peer confirmation was positively associated with e-learning motivation (β = 0.256, $p < 0.001$).
Conclusion: Within the proposed model, peer-to-peer confirmation showed the strongest association with e-learning motivation, indicating the relevance of supportive peer interaction for e-learning motivation.

KEYWORDS
anxiety, depression, e-learning, learning motivating factors, peer-to-peer confirmation, personality traits

Highlights

- Developed and tested an integrative model linking personality traits, mental health, peer-to-peer confirmation, and learning motivating factors in e-learning.

- Found that personality traits were associated with learning motivating factors in e-learning primarily indirectly via peer-to-peer confirmation.
- Mental health problems, while strongly linked to personality, did not mediate the personality—e-learning motivation relationship.
- Clear direction and reward and recognition emerged as the highest-rated motivation factors among participants.
- Results align with Self-Determination Theory, emphasizing the role of relatedness in sustaining motivation in online education.

1 Introduction

E-learning has become a central component of higher education worldwide, accelerated by the COVID-19 pandemic (Osei et al., 2022; Yahiaoui et al., 2022). While it offers flexibility and accessibility, it also poses challenges, particularly for maintaining student motivation (Berestova et al., 2022; Mekheimer, 2025). Motivation is one of the strongest correlates of persistence and achievement in digital environments (Hartnett, 2016). However, motivation in e-learning is not fixed; it is shaped by the interaction of individual and contextual factors (Ryan and Deci, 2000). In practice, reduced motivation in online settings may be reflected in lower engagement, weaker persistence, and difficulties in consistent learning routines.

The self-determination theory (SDT; Ryan and Deci, 2000) offers a strong framework for understanding motivation in digital contexts. Roca and Gagné (2008) applied SDT to e-learning context and reported that learners' intention to continue using e-learning platforms was strongly associated with autonomy, competence, and relatedness. In e-learning, these needs may be more difficult to satisfy, particularly relatedness, given reduced informal interaction and fewer social cues. Therefore, engagement and motivation may related to both personal resources (e.g., personality traits) and contextual resources (e.g., supportive peer interaction; Xie et al., 2017).

Previous studies have identified several key correlates of e-learning motivation, which can be grouped into three primary areas. The first area concerns stable individual differences, particularly the Big Five personality traits, which are associated with how students adapt to online environments (Fırat, 2023; Osei et al., 2022; Yeh et al., 2021). The second area is students' mental health, with multiple studies indicating that anxiety and depression are associated with lower e-learning motivation (Dirzyte et al., 2021a; Paechter et al., 2022; Yahiaoui et al., 2022). A third line of research highlights the role of the social context, where student-to-student confirmation and peer support have been identified as relevant factors in e-learning (Berestova et al., 2022; Dirzyte et al., 2021b; Fu et al., 2024; Hou et al., 2025; Yang et al., 2025; Zhu et al., 2025).

Moving from these broad influences to learning processes, we also considered the specific factors that shape student motivation in e-learning. The framework developed by Law et al. (2010) identifies six learning motivating factors, categorized into two intrinsic and four extrinsic factors. Intrinsic motivation focuses on the individuals rather than the environmental setting, whereas extrinsic motivation arises from the external learning environment (Ngan and Law, 2015). The intrinsic factors include individual attitude and expectation and challenging goals. The extrinsic factors include clear direction, reward and recognition, punishment, and social pressure and competition.

The first intrinsic factor, individual attitude and expectation, refers to students' beliefs about learning, their goals, and their confidence in their ability to succeed. The second intrinsic factor, challenging goals, highlights the motivational benefit of setting meaningful, demanding objectives that encourage students to improve. The extrinsic factors begin with clear direction, which relates to the presence of structured learning objectives, well-defined expectations, and guidance—elements that increase a students' ability to focus and engage with learning (Ramsden, 2003). The fourth factor, reward and recognition, includes feedback, praise, and grades that acknowledge students' progress (Ngan and Law, 2015). These extrinsic motivators may be associated with higher learning motivation when used appropriately; however, they may also be associated with lower motivation when perceived as controlling or excessive (Cameron et al., 2005). The fifth factor, punishment, refers to negative consequences such as failure or academic penalties. While these may drive short-term engagement, they can reduce motivation if overused (Law et al., 2010). Finally, the sixth factor, social pressure and competition, reflects the role of peer comparison and group expectations. According to Ngan and Law (2015), social pressure and competition can motivate students to perform better to maintain competence in group settings, a concept that aligns with Maslow (1943) esteem needs.

While the literature supports the relevance of personality traits, mental health, and peer support in e-learning, these factors are often investigated separately. Consequently, there is limited evidence from integrative models that examine these domains simultaneously and clarify how they are jointly associated with motivation in e-learning. Therefore, the present study addresses this gap by examining the relationships between the Big Five personality traits, mental health indicators (anxiety and depression), and peer-to-peer confirmation as correlates of e-learning motivation factors within a single analytic framework. This integrated approach aims to provide a more coherent account of how individual differences and peer interaction are associated with motivational factors in e-learning contexts.

2 Literature review and hypotheses development

2.1 Personality traits as correlates of e-learning motivation

Personality theory provides a foundation for understanding individual differences in motivation and learning. Several models have been proposed, including Eysenck's three-factor model (Boeree, 2006) and the Myers-Briggs Type Indicator (Myers et al., 1998), which classify personality based on temperament and cognitive preferences. This study used most widely accepted for its reliability and cross-cultural validity the Five-Factor Model (FFM; McCrae and John, 1992; Costa and McCrae, 2009), which consists of dimensions: extraversion (sociability, activeness, enthusiasm), agreeableness (compliance, generosity, altruism), conscientiousness (self-discipline, responsibility, achievement-striving), neuroticism (emotional instability, hostility, impulsivity), and openness to experience (curiosity, imagination; John and Srivastava, 1999). These traits have demonstrated associations with academic behaviors, motivation, and adaptation to online learning environments (Komarraju et al., 2011; Fırat, 2023). Dang et al. (2025)

found that personality traits influence engagement through emotion regulation. Personality traits linked to academic performance in traditional settings, such as conscientiousness, extraversion, agreeableness, and openness, also related to students' intention to complete online courses (Gupta, 2021).

Based on the Five-Factor Model (McCrae and Costa, 2008), previous research highlights conscientiousness as a strong positive correlate of online learning success due to its association with self-discipline and goal orientation (Fırat, 2023; Yeh et al., 2021), while openness to experience facilitates adaptability to innovative learning technologies (Osei et al., 2022). Also, conscientious learners favor organized study habits and advanced time management strategies (Moldasheva and Mahmood, 2014), while those high in neuroticism prefer highly structured environments (Furnham, 1992).

Meta-analyses demonstrated that conscientiousness, agreeableness and openness to experience are positively associated with academic performance (Mammadov, 2022; Vedel, 2014). Recent evidence shows that agreeableness, conscientiousness, and openness show stronger associations with learning outcomes compared to extraversion and neuroticism in online settings (Yu, 2021). Agreeableness tends to support cooperative behaviors, whereas neuroticism (negative emotionality) is negatively related to motivation, satisfaction, and performance—likely due to anxiety and stress in virtual settings (Dirzyte et al., 2021b). A longitudinal study (Tlili et al., 2023) found that extraversion and conscientiousness notably related to learners' navigation behaviors within an online course; extraverts gravitated toward peer interaction features, while conscientious students favored achievement-oriented paths.

Beyond global associations with academic achievement, several studies have examined how Big Five traits relate specifically to students' academic motivation. Ahmadi et al. (2023) found that higher extraversion, openness, and conscientiousness, and lower neuroticism, were associated with stronger academic motivation in paramedical students. McGeown et al. (2014) reported that conscientiousness, together with self-efficacy, predicted adolescents' academic motivation, whereas other traits played a smaller role. Mammadov et al. (2021) showed that Big Five traits, particularly conscientiousness, were linked to gifted students' autonomous academic motivation and achievement. Taken together, these studies suggest that more conscientious and less neurotic students tend to report higher levels of academic motivation. Evidence on extraversion in e-learning is mixed: online platforms may favor introverts by allowing greater reflection, whereas extraverts thrive when social interaction is facilitated (Denden et al., 2022). Empirical research supports these patterns. Fırat (2023) reported that extraversion, agreeableness, conscientiousness, and openness to experience were associated with e-learning autonomy, while neuroticism was not. Similarly, Denden et al. (2022) reported that extraversion and openness to experience were associated with user's attitudes and perception of ease of use, which in turn were associated with intention to use gamified systems. Other studies highlight that personality traits interact with technological attitudes and self-efficacy in shaping learning engagement (Osei et al., 2022). Baruth and Cohen (2022) confirmed positive relationships between conscientiousness and openness to experience with online course satisfaction. Quigley et al. (2022) found that personality traits significantly related to online engagement during the pandemic. Recent work in immersive digital learning environments further suggests that personality–engagement links may depend on learners' anxiety levels. For instance, metaverse education research indicates that anxiety can moderate how personality traits relate to student engagement and perceived learning, highlighting that affective states may condition the expression of trait dispositions in technology-rich learning contexts (Kim et al., 2025). A study of 301 first-year psychology students found that conscientiousness strongly linked all types of online engagement, while extraversion—to participation and performance. Agreeableness and openness to experience were linked to participation and emotional engagement, whereas neuroticism showed negative associations with engagement skills, emotional engagement, and performance (Quigley et al., 2022).

Despite these insights, the mechanisms through which personality is linked to e-learning motivation—particularly via mental health and peer support—remain unclear, highlighting the need for integrative models addressing these pathways.

2.2 Mental health challenges (anxiety, depression) as negative correlates of e-learning motivation

Students' mental health is strongly connected to their academic motivation, and the challenges of e-learning can increase existing problems or create new psychological difficulties. A growing body of evidence demonstrates a clear and consistent negative association between affective states—particularly anxiety, depression—and learning motivation in e-learning contexts (Dirzyte et al., 2021a; Fu et al., 2024; Yahiaoui et al., 2022). Anxiety and depression impair concentration and reduce persistence in academic tasks (Fu et al., 2024). Yaghi (2022) reported that students engaged in e-learning experience higher levels of stress and poorer mental health outcomes, including increased anxiety, depression, and overall psychological distress. These findings are consistent with earlier evidence indicating that cognitive overload and problem-solving frustration serve as major stressors in online learning environments (Robins et al., 2003). Similarly, Berestova et al. (2022) found that lack of peer interaction exacerbates stress, contributing to decreased motivation. Thus, mental health may act as a key mediator between personality and motivation. However, emerging evidence in student populations suggests that anxiety-related outcomes may be shaped through more proximal psychosocial mechanisms (e.g., self-evaluative and acceptance-related processes), reinforcing the value of testing mechanism-oriented pathways rather than relying only on bivariate associations (Chen and Lai, 2025).

Recent research is consistent with these negative patterns. For example, technostress dimensions such as techno-overload and work-home conflict have been reported to show indirect associations with anxiety and depression through lower intrinsic motivation (Marrinhas et al., 2023). These patterns also align with evidence that emotional fatigue is associated with lower satisfaction and academic commitment during prolonged online learning (Mamani-Benito et al., 2024).

Recent findings underscore the academic consequences of depression. Lin et al. (2025) found that among undergraduate students in eldercare programs, depression was positively associated with academic burnout. This relationship was partially mediated by self-efficacy and moderated by social support, indicating that higher perceived support can buffer symptoms of depression on academic outcomes. These findings align with prior Fu et al. (2024) research

demonstrating that positive emotions mediate between proactive personality and online learning engagement; higher levels of proactive personality and positive emotions correspond to higher levels of online learning engagement. Together, this evidence suggests that student-to-student confirmation is associated with indicators of mental health and psychological well-being in academic settings, consistent with the view that confirming peer communication may be linked to lower distress and higher well-being (LaBelle and Johnson, 2021).

Social isolation further compounds mental health challenges. A study of Polish healthcare students revealed that even after pandemic restrictions ended, persistently high levels of distress—including anxiety and depression—were linked to reduced peer interaction and perceived social isolation (Hisato et al., 2023). Similarly, technostress—especially when it is linked to digital devices and lack of instructional support—has been shown to increase cognitive fatigue and anxiety among university students, thereby damaging motivation and the quality of online learning (Saleem et al., 2024).

Social distance can increase feelings of worthlessness and lead to higher levels of worry, anxiety, and fatigue (Brooks et al., 2020). In contrast, social support, including student-to-student confirmation, is linked to better mental health and higher learning motivation (LaBelle and Johnson, 2021).

2.3 Peer-to-peer confirmation: a specific social support mechanism

Social interaction is a critical determinant of student motivation in e-learning. Social support is typically classified in three ways: by the type of assistance—such as emotional, instrumental, or experiential support (Lin and Kishore, 2021), by the source—such as peers, teachers, or parents (Gao et al., 2023; Martinot et al., 2022), and by context—such as settings in schools versus universities (Martinot et al., 2022). According to Benner et al. (2017), school belonging play buffering role to school engagement, and learners loneliness or depressive symptoms. University support plays a crucial role in enhancing the quality of e-learning (Azila-Gbettor et al., 2023) and has been identified as a significant association of international students' engagement in virtual education (Abubakari et al., 2022).

According to Self-Determination Theory (SDT; Ryan and Deci, 2000), teachers play a key role in supporting students' needs for autonomy and competence, while peer interaction are especially important for fulfill students' need for relatedness (Vasconcellos et al., 2020). This framework aligns with recent findings by Martinot et al. (2022), who reported that peers and teachers serve as key sources of social support in educational settings, particularly for fostering school engagement. Moreover, Martínez-López et al. (2023) emphasized the positive associations between perceived social support, self-regulated learning, and academic achievement in a large-scale study. A related meta-analysis by Martínez-López et al. (2024) confirmed a robust association between social support and self-regulated learning, further underscoring the relevance of supportive interactions for educational success. Together, these findings underscore that meaningful social interactions, especially in university and online contexts, are foundational to fostering engagement, persistence, and motivation in students.

SDT emphasizes the importance of supportive social contexts in fostering intrinsic motivation and perceived competence (Ryan and Deci, 2000). Recent empirical research confirms this theoretical proposition. For example, Yang et al. (2025) found that social support, self-regulated learning, and flow experiences significantly enhanced student e-learning engagement in self-directed online learning environments. These results underscore the motivational power of positive peer and instructional dynamics. Similarly, Ma and Chen (2025) demonstrated that teacher scaffolding, guided by SDT principles, significantly increased students' intrinsic motivation even in AI-mediated language learning platforms, highlighting the importance of human interaction in e-learning.

Student-to-student confirmation—a specific form of peer interaction—has gained recognition as a component of communication process in educational settings (Johnson and LaBelle, 2016, 2024). It refers to instances where students receive acknowledgment, assistance, or individualized attention from classmates (Kerimoğlu et al., 2023). Such affirming interactions help build a sense of belonging and competence, aligning closely with the principles of SDT (Deci and Ryan, 2012; Ryan and Deci, 2000). Positive peer interactions have been shown to improve satisfaction and engagement in e-learning (Mekheimer, 2025). In addition, Berestova et al. (2022) found that peer communication reduces feelings of isolation—a common barrier to motivation in online settings.

Despite its theoretical and practical importance, peer-to-peer confirmation is rarely integrated into broader associational models that simultaneously consider personality traits and mental health variables. Accordingly, to address this gap, the present study aims examines associations among personality traits, mental health (i.e., anxiety, depression), and peer-to-peer confirmation, and students' motivation in e-learning environments.

2.4 Present study

Although personality traits, mental health and peer support have each been examined in in e-learning (Fırat, 2023; Osei et al., 2022; Yahiaoui et al., 2022), evidence from integrative models than considerer these domains simultaneously remains limited, particularly within structural equation modeling (SEM) frameworks. Drawing on Self-Determination Theory (SDT) and the Five-Factor Model (FFM) of personality traits, the present study examined a structural model in which personality traits are associated with e-learning motivation factors directly and indirectly via mental health (anxiety and depression) and peer-to-peer confirmation. Peer-to-peer confirmation was conceptualized as a peer-related social process relevant to SDT's relatedness need (Ryan and Deci, 2000; Deci and Ryan, 2012; Ryan and Deci, 2022).

2.4.1 Study goal and research questions

Therefore, the goal of this study was to examine associations between personality traits and learning motivating factors in e-learning and to evaluate whether mental health (anxiety and depression) and peer-to-peer confirmation within an integrated structural model. To address this objective, we formulated the following research questions:

> RQ1: How are personality traits associated with learning motivating factors in e-learning?

RQ2: How are personality traits associated with anxiety and depression?

RQ3: How are anxiety and depression associated with learning motivating factors in e-learning?

RQ4: How is peer-to-peer confirmation associated with learning motivating factors in e-learning, and does it account for part of the association between personality traits and e-learning motivation?

Based on the theoretical framework and prior empirical findigs, we tested the following hypotheses (Figure 1):

H1: Personality traits extraversion, agreeableness, conscientiousness, and openness to experience are positively related to learning motivating factors in e-learning, whereas neuroticism is negatively related to e-learning motivating factors.

H2: Personality traits extraversion, agreeableness, conscientiousness and openness to experience are negatively related to anxiety, depression, while neuroticism is positively associated.

H3: Mental health variables (anxiety, depression) are negatively related to learning motivating factors in e-learning and partially mediates the relationship between personality traits and e-learning motivating factors.

H4: Personality traits extraversion, agreeableness, conscientiousness, and openness to experience are positively related to peer-to-peer confirmation, whereas neuroticism is negatively related to it.

H5: Peer-to-peer confirmation is positively related to e-learning motivation factors and partially mediates the relationship between personality and e-learning motivating factors.

3 Materials and methods

This study employed a correlational cross-sectional design to examine the relationships between personality traits (extraversion, agreeableness, conscientiousness, openness to experience, neuroticism), mental health variables (depression, anxiety), peer-to-peer confirmation (individual attention, acknowledgement, assistance), and e-learning motivation factors (individual attitude, challenging goals, clear direction, reward and recognition, punishment, social pressure and competition). Structural equation modeling (SEM) was used to test the proposed theoretical model and hypothesized indirect associations.

3.1 Sample

3.1.1 Participants and eligibility criteria

The initial sample consisted of 749 respondents. The analytic sample included participants who completed all study measures and provided usable data on the primary variables (final N = 595). Inclusion criteria were: (a) age ≥ 18 years, (b) current enrollment in an e-learning course/program (Lithuanian universities or Turing College), and (c) informed consent to participate. Exclusion criteria were: (a) age < 18 years and (b) incomplete responses on the core measures required for the correlational and SEM analyses (listwise exclusion of missing data for the main model).

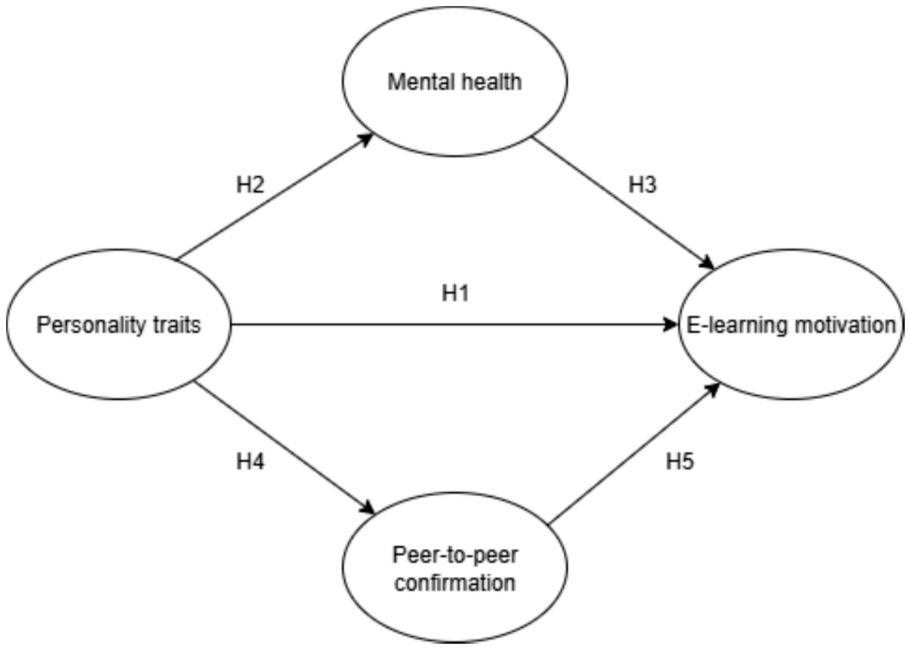


FIGURE 1
Model of the hypothesized associations between the study variables.

3.1.2 Age range justification

The analytic sample consisted of 33.3% males (n = 198) and 66.7% females (n = 397), with a mean age of 26.34 years (SD = 8.44; age range: 18–56). This broad age range reflects the heterogeneity of contemporary e-learning populations, which include both traditional university-age learners and non-traditional adult learners participating in online higher education and professional upskilling pathways. The age distribution was therefore retained to reflect typical e-learning cohorts in the study context.

3.1.3 Sample characteristics and generalizability

This study used a cross-sectional, correlational design to examine associations among personality traits, mental health indicators (anxiety and depression), peer-to-peer confirmation, and e-learning motivating factors. Participants were recruited through voluntary participation in an online survey distributed via e-learning courses and programs offered by multiple Lithuanian universities and Turing College. As the study relied on convenience sampling, findings should be interpreted as associations within the observed sample, and generalizability to the broader population of Lithuanian e-learners (and to other cultural or institutional contexts) may be limited. Demographic and academic characteristics of the sample (sex, age, education level, marital status, employment status, study level, and self-rated academic achievement) are presented in Supplementary Table S16.

3.2 Instruments

Five standardized instruments were used in this study. All instruments were translated into Lithuanian following standard forward–backward translation procedures. Initial Lithuanian versions were produced by bilingual experts, back-translated into English by independent translators, and discrepancies were resolved by consensus to ensure conceptual correspondence with the original scales.

3.2.1 Student-to-student confirmation

Peer-to-peer confirmation was assessed using the Student-to-Student Confirmation Scale (LaBelle and Johnson, 2018), comprising 25 items and three subscales:

- Individual Attention (10 items)—e.g., "My classmates express interest in getting to know me outside of class";
- Acknowledgement (9 items)—e.g., "My classmates tell me that they are impressed by my abilities";
- Assistance (6 items)—e.g., "My classmates are willing to help me study for tests".

Responses were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The overall internal consistency for the scale in this study was excellent (Cronbach's α = 0.965).

3.2.2 The PHQ-9

Depressive symptoms were assessed using the PHQ-9 (Kroenke et al., 2001), which includes 9 items rated on a 4-point Likert scale (0 = not at all to 3 = nearly every day). Total scores range from 0 to 27, with higher scores indicating more severe depressive symptoms. The PHQ-9 has shown strong reliability in previous studies (α = 0.87; Kroenke et al., 2001), and in this study, Cronbach's α = 0.888.

3.2.3 The GAD-7

Anxiety symptoms were measured with the GAD-7 (Spitzer et al., 2006), a 7-item scale widely used for screening generalized anxiety Items are rated from 0 (not at all) to 3 (nearly every day), with scores above 10 suggesting clinically relevant anxiety. The total score ranges from 0 to 21, with higher scores indicating more severe anxiety symptoms. The GAD-7 has demonstrated strong reliability: internal consistency of Cronbach's α = 0.89 (Spitzer et al., 2006), and in this study Cronbach's α = 0.908.

3.2.4 The learning motivating factors questionnaire

The Learning Motivating Factors Questionnaire (Law et al., 2010) includes 19 items assessing various motivational factors: individual attitude and expectation, challenging goals, clear direction, rewards and recognition, punishment, social pressure and competition. Items were rated on a 6-point Likert scale (1 = strongly disagree to 6 = strongly agree). Internal consistency in this study was Cronbach's α = 0.869.

3.2.5 BFI-2

Personality traits were assessed using the Big Five Inventory-2 (BFI-2) (Soto and John, 2017), which measures five dimensions: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. Items were rated on a 5-point Likert scale (1 = disagree strongly to 5 = agree strongly). Cronbach's alpha for the BFI-2 Short Form subscales in this study: extraversion subscale was 0,814; agreeableness—0,775; conscientiousness—0,834; neuroticism—0,905, openness to experience—0,658.

3.3 Data collection procedure

Prior to participation, students enrolled in various online learning programs were invited via email to voluntarily complete an online survey hosted on the secure platform (psytest.online; last accessed on August 20, 2025). The invitation email included an information sheet and an electronic consent form describing the study purpose, procedures, and ethical considerations. After providing informed consent, participants completed the questionnaire in a single online session. The survey included measures of learning motivating factors, personality traits, anxiety, depression, and peer-to-peer confirmation. Participation was voluntary and no incentives were provided. Ethical approval for the study was granted by the Institutional Review Board of Klaipeda University (Approval No. STIMC—BMTEK-P03, April 12, 2021).

3.4 Statistical analysis

To analyze the data, descriptive statistics and Pearson correlations were computed using SPSS v29.0 (IBM Corp., Armonk, NY, United States).

Prior to estimating the structural models, we conducted confirmatory factor analyses (CFAs) for all multi-item instruments (PHQ-9, GAD-7, BFI-2 traits, student-to-student confirmation, and Learning Motivating Factors) in JASP (version 0.95.4; JASP Team, University of Amsterdam). Symptom and motivation scales were analyzed using ML estimation, treating items as continuous indicators, whereas the BFI-2 traits were analyzed using a DWLS estimator based on polychoric correlations, given their ordinal 5-point response format. Summary CFA fit indices and reliability statistics (χ^2, CFI, TLI, RMSEA with 90% CI, SRMR, ω, α, AVE) are reported in the Results and Supplementary materials.

Primary structural equation modeling (SEM) analyses were then conducted in jamovi v2.6.13 using SEMLj (lavaan) with maximum likelihood estimation. The SEM models were used to evaluate the hypothesized direct and indirect associations among personality-related variance, mental health (anxiety and depressive symptoms), peer-to-peer confirmation, and e-learning motivating factors. Model fit was evaluated using χ^2, CFI, TLI, RMSEA (90% CI), and SRMR. Indirect effects were tested using bias-corrected bootstrapping with 2,000 resamples to generate 95% confidence intervals. For internal consistency and convergent validity of the retained latent constructs, SEMLj reliability indices were reported (Cronbach's α, McDonald's ω, and AVE). Finally, to assess robustness across software implementations and to support graphical presentation, the integrated model was also re-estimated in AMOS v26 (IBM SPSS AMOS), and the standardized pattern of relations was compared with the jamovi solution.

4 Results

Confirmatory factor analyses generally supported the intended latent structures, although model fit varied across instruments. For GAD-7, a one-factor CFA estimated with ML showed excellent incremental fit (CFI = 0.975, TLI = 0.962, SRMR = 0.029) and acceptable convergent validity (AVE = 0.595) and internal consistency (ω = 0.907; α = 0.908). The PHQ-9 one-factor model achieved adequate CFI but an elevated RMSEA (CFI = 0.921; RMSEA = 0.110), indicating misfit under a strict unidimensional specification in this sample. Student-to-student confirmation was modeled as three first-order factors under a second-order general factor; item loadings were uniformly high and reliability was excellent (total ω = 0.974; α = 0.965), although global fit was weak (CFI = 0.857; RMSEA = 0.115), consistent with potential item redundancy or model complexity effects. The Learning Motivating Factors scale showed borderline acceptable fit for a six-factor structure (CFI = 0.895; RMSEA = 0.083) and adequate-to-strong reliability across subscales (ω = 0.674–0.894). For the BFI-2, separate single-trait CFAs estimated with DWLS indicated good fit for Extraversion, Conscientiousness, and Neuroticism (CFI = 0.96–0.99; RMSEA ≈ 0.05–0.06) and acceptable but weaker fit for Agreeableness and Openness to experience (CFI ≈ 0.91–0.92; RMSEA ≈ 0.07), with internal consistency ranging from modest (ω = 0.678 for Agreeableness) to excellent (ω = 0.910 for Neuroticism).

4.1 Descriptive statistics and bivariate correlations

To address RQ1–RQ3 and provide preliminary analysis for H1, H2, and H4, we first report descriptive statistics and bivariate correlations among all study variables (Table 1; $N = 595$).

Overall, mean levels of e-learning motivating factors were relatively high, with particularly high scores for clear direction (M = 4.99, SD = 0.79) and reward and recognition (M = 4.87, SD = 0.94). Mean levels of anxiety (GAD-7; M = 6.48, SD = 5.08) and depression (PHQ-9; M = 8.05, SD = 5.97) were moderate. Peer-to-peer confirmation subscales ranged from 3.29 to 3.73.

The correlation analysis revealed several significant associations. Extraversion, agreeableness, conscientiousness, and openness to experience were positively significantly associated with learning motivation factors (r ranged from 0.08 to 0.39, $p < 0.01$). In contrast, neuroticism showed significant negative correlations with these factors (r ranged from −0.09 to −0.35, $p < 0.01$). Anxiety and depression were negatively related to both learning motivation ($r = -0.11$ to -0.39, $p < 0.01$) and peer-to-peer confirmation ($r = -0.09$ to -0.25, $p < 0.01$). Higher neuroticism scores were associated with higher anxiety and depression. Student-to-student confirmation scale and its subscales (individual attention, acknowledgement, and assistance) were significantly and positively correlated with learning motivation factors (r ranged from 0.13 to 0.27, $p < 0.01$) and with personality traits such as extraversion (r ranged from 0.27 to 0.33, $p < 0.01$) and conscientiousness ($r = 0.10$–0.16, $p < 0.01$), while showing significant negative correlations with anxiety ($r = -0.099$, $p < 0.05$) and depression ($r = -0.183$, $p < 0.01$). These patterns were consistent across the three subscales of the peer-to-peer confirmation measure: individual attention, acknowledgement, and assistance, all of which showed negative correlations with anxiety and depression ranging from −0.09 to −0.19. These preliminary findings informed the subsequent structural equation modeling analysis.

4.2 Main analysis

Structural equation modeling (SEM) was used to test the hypothesized relations among personality traits, mental health (anxiety and depressive symptoms), peer-to-peer confirmation, and e-learning motivating factors (H1–H5). A full latent SEM was specified according to the theoretical assumptions described in the Introduction. All primary SEM estimation and statistical inference were conducted in jamovi v2.6.13 using SEMLj (lavaan) with maximum likelihood estimation. IBM SPSS AMOS v26.0 was used to generate publication-quality path diagrams and as a robustness check by re-estimating the same model specification to verify that the standardized pattern of relations was consistent across software implementations. Where figures are presented, the coefficients displayed correspond to the jamovi standardized solution.

The analytic strategy proceeded sequentially: (a) estimation of a comprehensive initial SEM model, (b) evaluation of hypothesis-specific intermediate models, and (c) specification of a more parsimonious final integrated SEM model after excluding poorly performing indicators and factor loadings. Model evaluation followed Kline's three-step approach (2016), combining (i) the exact-fit χ^2 test, (ii) inspection of residuals, and (iii) interpretation of standardized coefficients (β), unstandardized estimates (B), standard errors (SE), and global fit indices (χ^2, df, CFI, TLI, RMSEA with 90% CI, SRMR).

TABLE 1 Means, standard deviations, and Pearson correlations of the study variables (N = 595).

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Extraversion	3.31	0.57															
2. Agreeableness	3.58	0.51	0.15**														
3. Conscientiousness	3.47	0.57	0.39**	0.28**													
4. Neuroticism	2.94	0.76	−0.30**	−0.25**	−0.35**												
5. Openness to experience	3.66	0.45	0.39**	0.12**	0.19**	0.03											
6. Individual attitude and expectation	4.72	0.84	0.25**	0.07	0.18**	−0.09*	0.14**										
7. Challenging goals	4.41	1.07	0.30**	0.15**	0.37**	−0.32**	0.19**	0.41**									
8. Clear direction	4.99	0.79	0.28**	0.12**	0.27**	−0.17**	0.19**	0.67**	0.48**								
9. Reward and recognition	4.87	0.94	0.11*	0.09*	0.06	0.04	0.04	0.55**	0.13**	0.50**							
10. Punishment	3.39	1.34	0.08	−0.02	−0.01	0.01	−0.08	0.26**	0.10*	0.25**	0.21**						
11. Social pressure and competition	3.46	1.18	0.12**	−0.05	0	−0.06	−0.06	0.25**	0.25**	0.21**	0.24**	0.43**					
12. Anxiety (GAD-7)	6.48	5.08	−0.11**	−0.16**	−0.24**	0.58**	0.07	−0.07	−0.27**	−0.13**	0.05	0	−0.04				
13. Depression (PHQ-9)	8.05	5.97	−0.19**	−0.17**	−0.32**	0.52**	0.03	−0.16**	−0.35**	−0.22**	−0.02	−0.01	−0.10*	0.56**			
14. Individual attention	3.73	0.79	0.31**	0.13**	0.14**	−0.18**	0.13**	0.19**	0.17**	0.25**	0.12**	0.13**	0.19**	−0.09*	−0.15**		
15. Acknowledgement	3.29	0.81	0.27**	0.06	0.17**	−0.18**	0.10*	0.19**	0.16**	0.21**	0.11**	0.10*	0.12**	−0.10*	−0.19**	0.65**	
16. Assistance	3.56	0.83	0.27**	0.08*	0.10*	−0.13**	0.11**	0.17**	0.11**	0.22**	0.09*	0.17**	0.13**	−0.06	−0.13**	0.69**	0.55**

N = 595. M, mean; SD, standard deviation. Pearson correlations are two-tailed. *$p < 0.05$; **$p < 0.01$.

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Detailed intermediate models and comparisons are reported in the Supplementary Tables S1–S15 and Supplementary Figures S1–S10.

4.2.1 Baseline SEM model

In the baseline structural equation model (SEM), we examined associations among a latent personality traits (indicated by extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience), latent mental health (indicated by anxiety and depression), latent Peer-to-peer confirmation (indicated by individual attention, acknowledgement, and assistance), and latent e-learning motivating factors (indicated by individual attitude and expectation, challenging goals, clear direction, reward and recognition, punishment, and social pressure and competition).

Model fit. Overall model fit was limited: $\chi^2(99) = 639$, $p < 0.001$, $\chi^2/df = 6.45$, RMSEA = 0.096 (90% CI [0.089, 0.103], RMSEA $p < 0.001$), CFI = 0.816, TLI = 0.777, IFI = 0.817, and SRMR = 0.084, suggesting that the baseline specification would benefit from refinement.

Structural model. At the structural level, peer-to-peer confirmation was a significant positive predictor of e-learning motivating factors (B = 0.257, SE = 0.054, $p < 0.001$; $\beta = 0.236$). The direct association between personality and learning motivating factors was not statistically significant (B = 0.496, SE = 0.278, $p = 0.074$; $\beta = 0.233$), and mental health was not associated with learning motivating factors (B = −0.001, SE = 0.023, $p = 0.966$; $\beta = -0.005$). Personality traits were positively associated with peer-to-peer confirmation (B = 0.604, SE = 0.107, $p < 0.001$; $\beta = 0.309$) and negatively associated with mental health (B = −9.571, SE = 0.956, $p < 0.001$; $\beta = -0.816$). Overall, these results indicate that peer-to-peer confirmation is the most proximal predictor of e-learning motivating factors in the baseline specification, whereas the direct path from mental health to motivation was non-significant and close to zero.

Measurement model. E-learning motivating factors were most strongly indicated by clear direction ($\beta = 0.831$) and individual attitude and expectation ($\beta = 0.818$), with comparatively weaker loadings for punishment ($\beta = 0.324$) and social pressure and competition ($\beta = 0.332$). Peer-to-peer confirmation was strongly reflected by individual attention ($\beta = 0.897$), assistance ($\beta = 0.764$), and acknowledgement ($\beta = 0.721$). Mental health was reflected similarly by anxiety ($\beta = 0.745$) and depression ($\beta = 0.746$). For personality, the strongest indicators neuroticism ($\beta = -0.799$), extraversion ($\beta = 0.533$), and conscientiousness ($\beta = 0.508$), whereas agreeableness showed a more modest loading ($\beta = 0.331$) and openness to experience was weak and not statistically significant ($\beta = 0.043$, $p = 0.589$). Robustness check (AMOS vs. jamovi). As a robustness check, we re-estimated the same baseline model in AMOS. The standardized pattern of effects was highly consistent with the jamovi solution (e.g., personality traits → peer-to-peer confirmation: $\beta \approx 0.31$; personality traits → mental health: $\beta \approx -0.82$; peer-to-peer confirmation → e-learning motivating factors: $\beta \approx 0.23$–0.24; mental health → e-learning motivating factors: $\beta \approx 0$). However, inference based on unstandardized coefficients and associated standard errors were not fully comparable across software implementations, consistent with differences in default latent-variable scaling/parameterization and standard error computation. Accordingly, primary inference is reported from jamovi/lavaan, while AMOS is used for robustness checking and visualization. Importantly, the substantive interpretation based on the standardized pattern of effects remained unchanged across platforms: peer-to-peer confirmation showed a robust positive association with e-learning motivating factors, whereas the direct effect of mental health on e-learning motivating factors was negligible.

Mediation (baseline model). Indirect effects were examined through peer-to-peer confirmation and mental health. The indirect association between personality and e-learning motivating factors via peer-to-peer confirmation was statistically significant (B = 0.155, SE = 0.041, $p < 0.001$; $\beta = 0.073$), whereas the indirect pathway via mental health was not supported (B = 0.009, SE = 0.221, $p = 0.966$; $\beta = 0.004$). Given the limited global fit of the baseline model, we proceeded with hypothesis-specific models (H1–H5) to identify the most stable indicators and relations, which then informed the parsimonious integrated SEM reported in Section 4.3.

Taken together, the baseline SEM model (estimated in jamowi) supported a robust association between peer-to-peer confirmation and learning motivating factors in e-learning, while indicating that a stepwise respecification strategy (H1–H5) and a subsequent parsimonious integrated SEM were warranted. Full regression weights (B, β, SE/CR/p) are presented in Supplementary Table S1, and the full baseline SEM diagram is shown in Figure 2.

4.2.2 The relationships between personality traits and e-learning motivation

To test H1, which presumed, that personality traits are associated with e-learning motivating factors, we tested primary (full) correlated-factors model with personality traits indicated by the five traits (extraversion, agreeableness, conscientiousness, neuroticism, openness to experience) and e-learning motivating factors indicated by six items (individual attitude and expectation, challenging goals, reward & recognition, clear direction, punishment, social pressure and competition; see Supplementary Figure S1). Model fit was limited: $\chi^2(43) = 398$, $p < 0.001$; CFI = 0.774; TLI = 0.710; RMSEA = 0.118 (90% CI [0.107, 0.128]); SRMR = 0.081. Notably, the standardized loadings for punishment ($\beta = 0.318$) and social pressure and competition ($\beta = 0.325$) were comparatively weak, whereas clear direction ($\beta = 0.830$) and individual attitude and expectation ($\beta = 0.820$) were strong. Despite suboptimal global fit, the latent association between personality traits and e-learning motivating factors was positive and statistically significant ($\varphi = 0.410$, unstd. Covariance B = 0.099, SE = 0.016, z = 6.23, $p < 0.001$).

Guided by these diagnostics, we retained the four strongest e-learning motivating factors (challenging goals, reward and recognition, clear direction, and individual attitude and expectation) and removed punishment and social pressure and competition due to low loadings. The retained correlated-factors model (personality traits with five indicators; e-learning motivating factors with four indicators) showed improved comparative fit and lower SRMR: χ^2 (26) = 249, $p < 0.001$; CFI = 0.833; TLI = 0.769; RMSEA = 0.120 (90% CI [0.107, 0.134]); SRMR = 0.076. In this retained model, clear direction ($\beta = 0.851$) and individual attitude and expectation ($\beta = 0.806$) showed the strongest loadings on e-learning motivation, followed by reward and recognition ($\beta = 0.585$) and challenging goals ($\beta = 0.522$). The latent correlation between personality traits and learning motivating factors in e-learning in this retained model was positive and statistically significant: $\varphi = 0.427$, unstd. Covariance B = 0.103, SE = 0.016, z = 6.38, $p < 0.001$, providing support to H1.

A compact model-fit summary for both the primary and retained models is provided in Supplementary Table S3, the baseline full

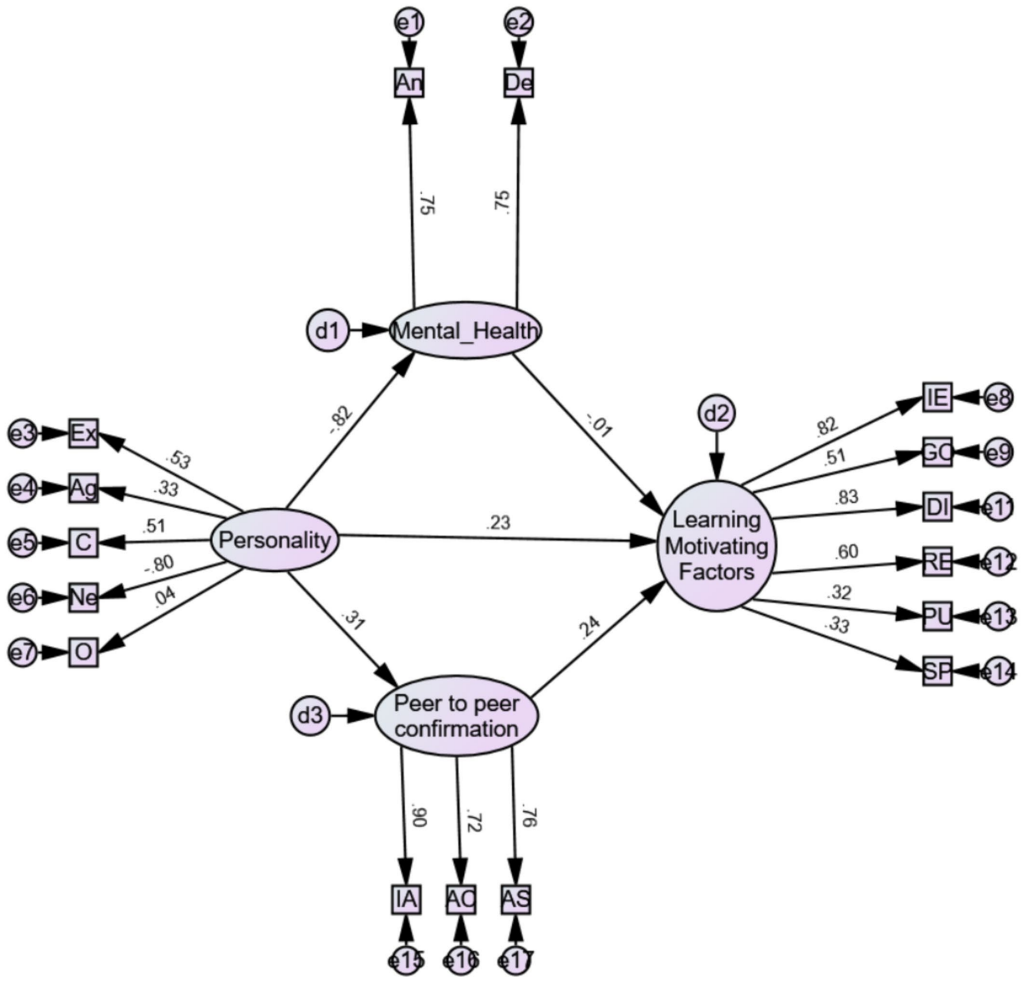


FIGURE 2
Baseline SEM model showing relationships between personality traits, mental health, peer-to-peer confirmation, and learning motivation factors in e-learning (standardized coefficients shown).

diagram is presented as Supplementary Figure S1, and the retained correlated-factors model is provided as Supplementary Figure S2. Full regression weights (unstandardized B and standardized β, with SE, CR, and p values) for the SEM primary model to H1 are presented in Supplementary Table S1. The corresponding weights for the retained H1 correlated-factors model reported in Supplementary Table S3. Model fit indices for the primary and retained H1 correlated-factors models are summarized in Supplementary Table S5.

4.2.3 The relationships between personality traits and mental health

In H2, we hypothesized that extraversion, agreeableness, conscientiousness, and openness to experience are negatively related to mental health variables (anxiety and depression), while neuroticism is positively associated. We first estimated a primary SEM model with all five personality traits and two mental health indicators. The model fit was limited: χ^2 (13) = 192, $p < 0.001$; CFI = 0.808; TLI = 0.690 35; RMSEA = 0.152 (90% CI [0.133, 0.171]); SRMR = 0.083. Although loadings were directionally consistent with H2, openness to experience did not load significantly on the personality traits factor (B = −0.0249, $p = 0.771$; $\beta = -0.013$), whereas neuroticism loaded strongly and in the expected (opposite) direction (B = −2.2647, $p < 0.001$; $\beta = -0.860$), and conscientiousness and agreeableness showed moderate positive loadings ($\beta = 0.455$ and $\beta = 0.307$, respectively). Mental health indicators loaded well: anxiety B = 8.130, SE = 0.580, z = 14.014, $p < 0.001$, $\beta = 0.768$; depression $\beta = 0.723$. The latent association between personality traits and mental health in this full specification was negative and large (B = −0.1144, SE = 0.0143, z = −8.02, $p < 0.001$; φ = −0.826), indicating that higher conscientiousness and agreeableness, lower neuroticism were related to lower anxiety and depression symptoms.

Guided by diagnostics and theory, we simplified the measurement of personality traits. A three-indicator model of personality traits (extraversion, conscientiousness, neuroticism) improved comparative fit but still required refinement: χ^2 (4) = 68.6, $p < 0.001$, CFI = 0.916, TLI = 0.791, RMSEA = 0.165 (90% CI [0.132, 0.200]), SRMR = 0.055. Although SRMR was acceptable, the combination of low TLI (< 0.90) and elevated RMSEA (> 0.08) indicated substantive misfit. All standardized loadings were statistically significant ($p < 0.001$), Within the retained personality traits measurement, neuroticism showed the strongest loading ($\beta = -0.876$, $R^2 \approx 0.767$; B = −2.349, SE = 0.242, $z = -9.70$, $p < 0.001$), while extraversion ($\beta = 0.469$, $R^2 \approx 0.220$) and conscientiousness ($\beta = 0.434$, $R^2 \approx 0.188$; B = 0.875, SE = 0.112, $z = 7.83$, $p < 0.001$) were moderate indicators were moderate indicators. Mental health was adequately represented by depression

($\beta = 0.719$, $R^2 \approx 0.517$) and anxiety (B = 8.220, SE = 0.584, $z = 14.07$, $p < 0.001$; $\beta = 0.772$, $R^2 \approx 0.596$).

The concurring model, defining personality traits with two indicator, conscientiousness and neuroticism (with a negative loading), showed markedly better comparative fit: χ^2 (1) = 8.77, $p = 0.003$; CFI = 0.987; TLI = 0.922; SRMR = 0.019; RMSEA = 0.114 (90% CI [0.054, 0.189]), noting the usual df = 1 caveat for RMSEA. All loadings were strong and significant ($p < 0.001$): conscientiousness $\beta = 0.413$ ($R^2 \approx 0.17$), and neuroticism $\beta = -0.837$ ($R^2 \approx 0.70$); on personality traits; depression $\beta = 0.716$ ($R^2 \approx 0.51$) and anxiety $\beta = 0.776$ ($R^2 \approx 0.60$) on mental health. The latent association between personality traits and mental health was negative and large (unstandardized B = −0.0984, SE = 0.0143, $z = -6.87$, $p < 0.001$; standardized φ = −0.878), indicating that higher conscientiousness and lower neuroticism were related to lower anxiety and depression symptoms, consistent with H2.

Full regression weights (unstandardized B and standardized β, with SE, z, and p values) for these H2 models are provided in Supplementary Tables S6–S8, and model fit indices for the primary, three-indicator, and retained specifications are summarized in Supplementary Table S5; corresponding diagrams are shown in Supplementary Figures S3–S5.

4.2.4 Relationships between mental health and e-learning motivating factors

To test H3 (mental health variables, anxiety and depression, are negatively related to e-learning motivating factors), we first estimated a primary correlated-factors model with mental health indicated by anxiety and depression, and e-learning motivation indicated by six factors (individual attitude and expectation, challenging goals, clear direction, reward & recognition, punishment, social pressure and competition). Model fit was limited: χ^2 (19) = 240, $p < 0.001$; CFI = 0.829; TLI = 0.748; RMSEA = 0.140 (90% CI [0.124, 0.156]); SRMR = 0.082. Loadings on e-learning motivation were consistent with prior analyses (e.g., clear direction $\beta = 0.819$; individual attitude & expectation $\beta = 0.830$), while punishment ($\beta = 0.322$) and social pressure & competition ($\beta = 0.331$) were relatively weak. Mental health indicators showed a moderate loading for anxiety ($\beta = 0.537$) and a Heywood symptom for depression (standardized loading > 1 and non-significant residual variance), which, together with the elevated RMSEA, suggested the need for refinement. The latent correlation between mental health and e-learning motivating factors was negative and small-to-moderate (unstandardized B = − 0.42 85, SE = 0.1588, $z = -2.699$, $p = 0.007$; standardized φ = − 0.226), consistent with H3.

Guided by these diagnostics and Kline's three-step procedure (Kline, 2016), we re-specified e-learning motivation with four strongest learning motivating factors (individual attitude & expectation, challenging goals, clear direction, reward & recognition). The retained H3 SEM model showed improved comparative fit though absolute fit remained limited: χ^2 (8) = 123, $p < 0.001$; CFI = 0.894; TLI = 0.802; RMSEA = 0.155 (90% CI [0.132, 0.180]); SRMR = 0.089. All standardized factor loadings were significant ($p < 0.001$). Measurement quality for e-learning motivation remained strong (clear direction $\beta = 0.838$; individual attitude and expectation $\beta = 0.821$; reward & recognition $\beta = 0.596$; challenging goals $\beta = 0.508$), and mental health indicators: depression $\beta = 1.021$; anxiety $\beta = 0.544$. The latent correlation stayed negative and small-to-moderate (unstandardized B = −0.1216, SE = 0.0249, $z = -4.878$, $p < 0.001$; standardized φ = −0.235), supporting H3. We note that the depression residual variance remained near zero (a mild Heywood feature), so we emphasize the CFI/TLI/SRMR profile and the convergent pattern across H3 specifications. Composite reliability was acceptable for both constructs: mental health Cronbach's $\alpha = 0.714$, $\omega = 0.787$, AVE = 0.669; learning motivating factors Cronbach's α = 0.769, ω = 0.791, AVE = 0.497.

Although the indirect pathway involving mental health was examined in the full integrated SEM, these results provide preliminary evidence consistent with H3 at the bivariate level: mental health indicators were negatively associated with e-learning motivating factors. However, the magnitude and statistical significance of this association may differ once personality traits and peer-to-peer confirmation are modeled simultaneously.

Full regression weights (unstandardized B and standardized β, with SE, z, and p values) for the H3 models are provided in Supplementary Tables S9, S10, and a model-fit summary is presented in Supplementary Table S5. The corresponding path diagrams are shown Supplementary Figures S6, S7.

4.2.5 Relationships between personality traits and peer-to-peer confirmation

To test H4, we first estimated a primary structural equation model with personality traits indicated by five variables (extraversion, agreeableness, conscientiousness, neuroticism, openness to experience), and peer-to-peer confirmation indicated by three factors: individual attention, acknowledgement, and assistance. Model fit was acceptable but refinement: χ^2 (19) = 105, $p < 0.001$; CFI = 0.928; TLI = 0.894; RMSEA = 0.087 (90% CI [0.071, 0.104]); SRMR = 0.047. All standardized loadings were statistically significant ($p < 0.001$). For personality traits: extraversion ($\beta = 0.772$, $R^2 \approx 0.60$), conscientiousness ($\beta = 0.560$; $R^2 \approx 0.31$), and negative emotionality ($\beta = -0.527$; $R^2 \approx 0.28$), whereas open-mindedness was negligible and non-significant ($\beta = -0.013$). Peer-to-peer confirmation was well represented by individual attention ($\beta = 0.898$; $R^2 \approx 0.81$), assistance ($\beta = 0.764$; $R^2 \approx 0.58$), and acknowledgement ($\beta = 0.720$; $R^2 \approx 0.52$). The latent association between personality traits and peer-to-peer confirmation was positive and moderate (B = 0.122, SE = 0.0173, z = 7.06, $p < 0.001$; φ = 0.416).

Guided by indicator strength and parsimony, we retained the two most robust personality indicators, extraversion and conscientiousness, and re-estimated the model (peer-to-peer confirmation remained indicated by three indicators). The retained model fit the data excellent: χ^2 (4) = 6.74, $p = 0.182$; CFI = 0.998; TLI = 0.994; SRMR = 0.015; RMSEA = 0.031 (90% CI [0.000, 0.075]). All loadings were significant and strong ($p < 0.001$): extraversion $\beta = 0.938$ ($R^2 \approx 0.88$) and conscientiousness $\beta = 0.436$ ($R^2 \approx 0.19$) on personality traits; individual attention $\beta = 0.895$ ($R^2 \approx 0.80$), acknowledgement $\beta = 0.720$ ($R^2 \approx 0.52$), and assistance $\beta = 0.767$ ($R^2 \approx 0.59$), on peer-to-peer confirmation. The latent correlation between personality traits and peer-to-peer confirmation remained positive (φ = 0.379; unstandardized B = 0.1362, SE = 0.0185, $z = 7.35$, $p < 0.001$), supporting H4. Reliability was good for peer-to-peer confirmation (CR/ω ≈ 0.84; AVE ≈ 0.64) and modest for the two-indicator personality construct (CR/ω ≈ 0.65; AVE ≈ 0.51).

Full regression weights (unstandardized B and standardized β, with SE, z, p values) are provided in Supplementary Tables S11, S12, and model-fit indices for both specifications are summarized in

Supplementary Table S5. The corresponding path diagrams are shown Supplementary Figures S7, S8.

4.2.6 Relationships between peer-to-peer confirmation to e-learning motivating factors

To test H5, that peer-to-peer confirmation is positively related to e-learning motivating factors, we estimated a primary correlated-factors model with peer-to-peer confirmation indicated by individual attention, acknowledgement, and assistance, and e-learning motivating factors indicated by six indicators (individual attitude and expectation, challenging goals, clear direction, reward and recognition, punishment, social pressure & competition). Model fit was limited: χ^2 (26) = 200, $p < 0.001$; CFI = 0.901; TLI = 0.863; RMSEA = 0.106 (90% CI [0.093, 0.120]); SRMR = 0.060. Loadings were for peer-to-peer confirmation: individual attention $\beta = 0.898$, acknowledgement $\beta = 0.718$, assistance $\beta = 0.765$; for e-learning motivating factors: individual attitude and expectation $\beta = 0.829$, challenging goals $\beta = 0.496$, clear direction $\beta = 0.820$, reward & recognition $\beta = 0.609$, punishment $\beta = 0.329$, social pressure and competition $\beta = 0.336$. The latent association between peer-to-peer confirmation and e-learning motivating factors was positive and small-to-moderate (unstandardized B = 0.151, SE = 0.0248, z = 6.08, $p < 0.001$; standardized φ = 0.307). The combination of low TLI and elevated RMSEA suggested that a more parsimonious specification was warranted.

To improve parsimony and fit, we retained all peer-to-peer confirmation indicators (acknowledgement, assistance, individual attention) and restricted e-learning motivating factors to four indicators (challenging goals, reward and recognition, clear direction, individual attitude and expectation). The respecified model fit well: χ^2 (13) = 69.20, $p < 0.001$; CFI = 0.964; TLI = 0.941; SRMR = 0.042; RMSEA = 0.085 (90% CI [0.066, 0.105]). All standardized loadings were significant ($p < 0.001$) and strong: Peer-to-peer confirmation: acknowledgement $\beta = 0.718$ ($R^2 = 0.516$), assistance $\beta = 0.765$ ($R^2 = 0.585$), individual attention $\beta = 0.899$ ($R^2 = 0.807$); Motivation: challenging goals $\beta = 0.498$ ($R^2 = 0.248$), reward & recognition $\beta = 0.601$ ($R^2 = 0.361$), clear direction $\beta = 0.838$ ($R^2 = 0.703$), individual attitude & expectation $\beta = 0.822$ ($R^2 = 0.675$). The latent association remained positive and significant (unstandardized B = 0.106, SE = 0.020, z = 5.32, $p < 0.001$; standardized φ = 0.298). Reliability was acceptable to good (Peer: α = 0.834, ω = 0.839, AVE = 0.636; Motivation: α = 0.769, ω = 0.791, AVE = 0.497).

Full regression weights (unstandardized B and standardized β, with SE, z, and p values) for the H5 models are provided in Supplementary Tables S13, S14, and model-fit indices are summarized in Supplementary Table S5; corresponding diagrams appear in Supplementary Figures S9, S10.

4.3 The integrated structural equation model

To test all hypothesized relations simultaneously (H1-H5), we estimated an integrated SEM that retained the best-performing indicators from the preceding measurement diagnostics. Although personality traits were assessed and are reported in the correlational and hypothesis-specific models, the personality factor in the integrated SEM was operationalized parsimoniously using conscientiousness (positive loading) and neuroticism (reverse-valenced, negative loading), consistent with the measurement diagnostics reported in Section 4.2.3 (e.g., openness to experience did not load significantly in the full H2 specification). Mental health was modeled using anxiety and depression; peer-to-peer confirmation was modeled using individual attention, acknowledgement, assistance; e-learning motivating factors were modeled using individual attitude and expectation, clear direction, challenging goals, reward and recognition. Overall fit was acceptable: χ^2 (39) = 221, $p < 0.001$; CFI = 0.921; TLI = 0.888; RMSEA = 0.089 (90% CI [0.077, 0.100]), RMSEA $p < 0.001$, and SRMR = 0.075.

Measurement model explained variance and reliability. All retained factor loadings were statistically significant ($p < 0.001$). Peer-to-peer confirmation was strongly reflected by individual attention ($\beta = 0.898$; $R^2 = 0.806$), acknowledgement ($\beta = 0.721$; $R^2 = 0.520$), and assistance ($\beta = 0.764$; $R^2 = 0.584$). E-learning motivating factors were indicated by individual attitude and expectation ($\beta = 0.808$; $R^2 = 0.653$), clear direction ($\beta = 0.852$; $R^2 = 0.726$), challenging goals ($\beta = 0.514$; $R^2 = 0.264$), and reward and recognition ($\beta = 0.588$; $R^2 = 0.346$). Mental health was measured by anxiety ($\beta = 0.762$; $R^2 = 0.581$) and depression ($\beta = 0.729$; $R^2 = 0.531$). Personality traits showed a positive loading on conscientiousness ($\beta = 0.429$) and a negative loading on neuroticism ($\beta = -0.821$; $R^2 = 0.674$).

For internal consistency and convergent validity, SEMLj reliability indices indicated good reliability for peer-to-peer confirmation (α = 0.834; ω = 0.837; AVE = 0.633) and modest reliability for mental health (α = 0.250; ω = 0.611; AVE = 0.555). Learning motivating factors showed acceptable internal consistency (α = 0.713; ω = 0.696), but low convergent validity (AVE = 0.284), consistent with comparatively weaker indicators (challenging goals; reward and recognition). The two-indicator personality factor showed very limited reliability (α = 0.072; ω = 0.030; AVE = 0.321); therefore, interpretations involving this latent construct should be treated as parsimonious and model-driven, rather than as a comprehensive representation of the full Big Five domain. Because mental health and personality were modeled with only two indicators, Cronbach's α is expected to be less stable and can underestimate reliability; accordingly, internal consistency is interpreted primarily using McDonald's ω alongside AVE for convergent validity.

Structural relations and mediation. As hypothesized, personality traits was positively related to peer-to-peer confirmation (B = 0.624, SE = 0.147, $\beta = 0.243$, $p < 0.001$) and negatively related to mental health (B = −14.018, SE = 1.848, $\beta = -0.889$, $p < 0.001$). Peer-to-peer confirmation was statistically significantly positively related to e-learning motivating factors (B = 0.275, SE = 0.058, $\beta = 0.256$, $p < 0.001$). In contrast, the direct paths of mental health to e-learning motivating factors ($p = 0.957$) and from personality traits to e-learning motivating factors ($p = 0.977$) were not statistically significant in the integrated model. Bias-corrected bootstrap tests (2,000 resamples) indicated a significant indirect association between personality traits and e-learning motivating factors via peer-to-peer confirmation (indirect B = 0.171, SE = 0.053, 95% CI [0.085, 0.294], $p = 0.001$; standardized indirect $\beta = 0.062$), whereas the indirect path via mental health was not significant ($p = 0.952$). Accordingly, the final results are most consistent with an indirect-only pathway from personality traits (conscientiousness and neuroticism) to learning motivating factors in e-learning via peer-to-peer confirmation in this specification (interpreted as statistical mediation given the cross-sectional design).

Standardized coefficients (β) are reported in Figure 3 (AMOS diagram shown for visualization and robustness), whereas unstandardized estimates (B), standard errors (SE), and p values from the primary jamovi (SEMLj/lavaan) analyses are reported in Supplementary Table S15. Indirect effects were tested using bias-corrected bootstrapping (2,000

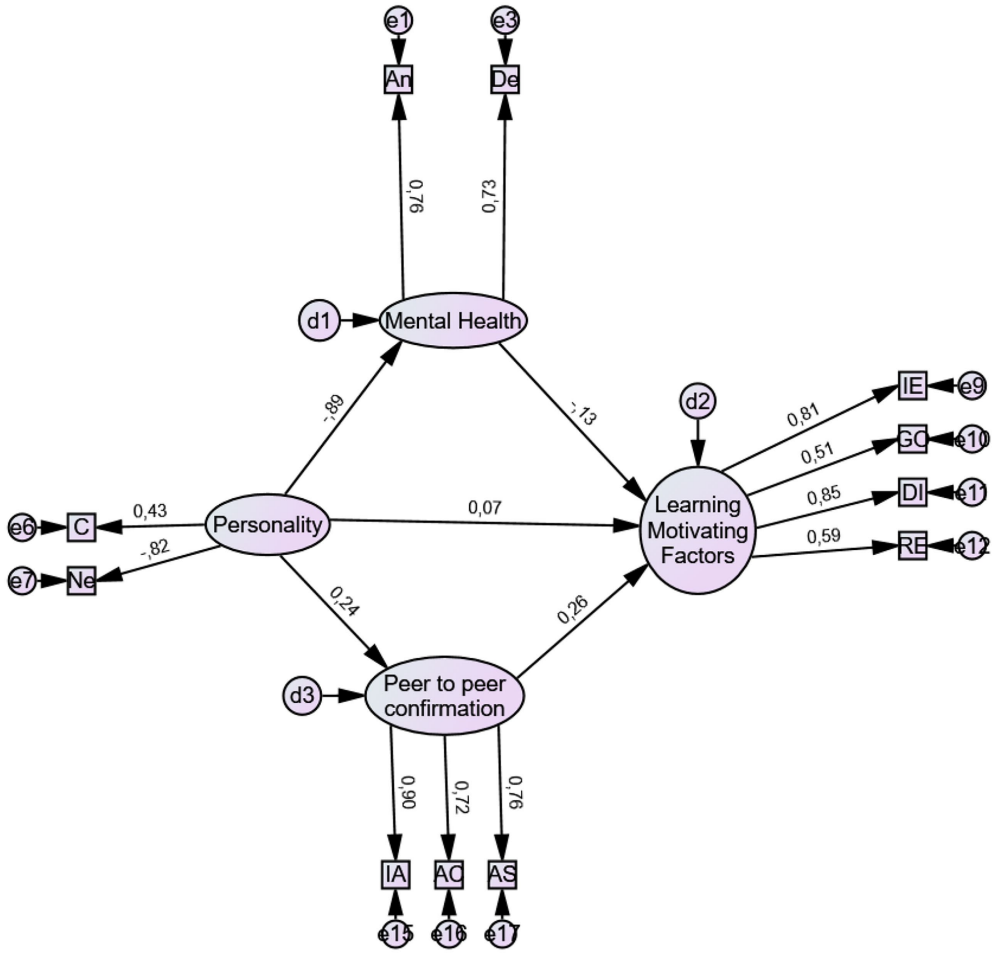


FIGURE 3
Integrated SEM model showing standardized associations among personality-related variance (neuroticism, conscientiousness), mental health (depression, anxiety), peer-to-peer confirmation (individual attention, acknowledgement, assistance), and e-learning motivating factors (individual attitude and expectation, challenging goals, reward and recognition, clear direction).

resamples) with 0.95 confidence intervals (Supplementary Table S16). For example, peer-to-peer confirmation was positively associated with e-learning motivating factors (B = 0.275, SE = 0.058, $p < 0.001$).

Standardized coefficients (β) are reported in Figure 3 (AMOS diagram shown for visualization and robustness), whereas unstandardized estimates (B), standard errors (SE), z values, and p values from the primary jamovi (SEMLj/lavaan) analyses are reported in Supplementary Table S15, provides unstandardized coefficients (B), with SE/CR/p, and tests for all paths (e.g., peer-to-peer confirmation → e-learning motivating factors: B = 0.275, SE = 0.058, $p < 0.001$, $\beta = 0.2561$). Indirect effects were tested using bias-corrected bootstrapping (2,000 resamples) with 95% confidence intervals.

5 Discussion

This present study examined relationships among personality traits, mental health indicators (anxiety and depression symptoms), peer-to-peer confirmation, and learning motivating factors in an e-learning context, guided by Self-Determination Theory (SDT; Deci and Ryan, 2012). At the bivariate level, personality traits, mental health indicators, and peer-to-peer confirmation were significantly associated with e-learning motivating factors, consistent with RQ1–RQ3 and providing preliminary support for H1, H2, and H4. In the integrated SEM, peer-to-peer confirmation showed a robust positive association with learning motivating factors in e-learning, and the indirect pathway from personality traits to learning motivating factors in e-learning via peer-to-peer confirmation was supported, whereas the indirect pathway via mental health was not supported in the final integrated model.

5.1 Personality traits and e-learning motivation

Our results are consistent with prior research showing that personality traits—such as extraversion, agreeableness, conscientiousness, and openness to experience—are positively associated with learning motivation (Fırat, 2023; Yeh et al., 2021; Osei et al., 2022). Correlation analyses showed that these personality traits were significantly and positively related to e-learning motivating factors, such as clear direction, challenging goals, and reward and recognition. Neuroticism, in contrast, was negatively associated with these motivational components, consistent with evidence that neuroticism is associated with lower persistence and satisfaction in online learning (Dirzyte et al., 2021b; Osei et al., 2022). These results support the

conceptualization of motivation in e-learning as substantially shaped by internal self-regulatory resources, particularly when learners perceive their environment as clear and socially responsive.

Methodologically, our SEM results highlight a trade-off between theoretical breadth and measurement stability when modeling personality traits in an integrated framework. While the hypothesis-specific models initially treated the full Big Five as indicators of a broader latent personality factor, the final integrated SEM operationalized personality parsimoniously using conscientiousness and neuroticism (reverse-valenced), consistent with the measurement diagnostics (e.g., openness to experience did not load significantly in the full H2 specification). Given the modest internal consistency/composite reliability of this two-indicator specification in the final model, this latent factor should be interpreted as a parsimonious proxy capturing the most stable personality-related variance in the dataset rather than as a comprehensive representation of the Big Five. Importantly, the substantive conclusions are based on the pattern of structural relations and bootstrap inference, rather than on treating the two-indicator personality factor as an exhaustive measure of personality traits.

Recent evidence from immersive digital learning environments further suggests that the links between personality traits and engagement-related outcomes may depend on anxiety. In metaverse education, anxiety has been shown to moderate how personality traits relate to student engagement and perceived learning, highlighting that affective states can condition the expression of trait dispositions in technology-rich learning contexts (Kim et al., 2025).

In line with SDT, personality traits may be linked to the satisfaction of psychological needs, particularly relatedness, by promoting positive social interactions. Our findings align with studies indicating that associations between personality and academic outcomes are often accounted for by contextual and interpersonal variables (Gupta, 2021; Tlili et al., 2023). These results also extend SDT by suggesting that autonomy in online learning is most strongly associated when competence and relatedness are simultaneously supported (Capon-Sieber et al., 2022).

Conscientiousness consistently emerges as the personality trait most strongly associated with positive outcomes in online learning. Bhattacharjee and Ramkumar (2025) reported that conscientiousness is a strongly associated with academic success, which is consistent with prior research on self-discipline and goal setting. Research demonstrates robust associations between conscientiousness and online learning satisfaction, motivation, and academic performance (Fırat, 2023; Yeh et al., 2021). These associations are commonly linked to self-discipline, organization, and achievement striving, which are critical in autonomous digital learning environments (Komarraju et al., 2011). Conscientious students tend to manage time effectively, set and pursue goals, and self-regulate their learning, and all these behaviors are associated with higher learnin motivation (Dang et al., 2025; Tlili et al., 2023). Recent evidence from online-course analytics further supports this interpretation: personality traits (including conscientiousness) have been linked to distinct navigational behavior patterns in online courses, suggesting that trait-related differences may manifest through learning behaviors rather than only through direct motivational associations (Tlili et al., 2023). Evidence further suggests that conscientiousness strengthens academic self-efficacy, reinforcing persistence and engagement in e-learning contexts (Osei et al., 2022). Some scholars argue that online learning may require higher levels of conscientiousness than traditional instruction to achieve comparable outcomes (Moldasheva and Mahmood, 2014).

Neuroticism demonstrates a consistent negative association with e-learning motivating factors, satisfaction, and performance (Fırat, 2023; Tlili et al., 2023). Characterized by heightened emotional instability and anxiety, students high in neuroticism may perceive challenges in e-learning, such as technical issues, ambiguity, and social isolation (Dirzyte et al., 2021b). This vulnerability often results in increased stress, diminished self-efficacy, and maladaptive motivational patterns, which may undermine engagement and persistence (Dang et al., 2025). The relative lack of immediate reassurance in virtual environments can further intensify this anxiety, potentially making sustained motivation less likely. Relatedly, evidence from pandemic-era online learning suggests that personality traits and stress perception jointly predict students' online engagement, which is consistent with the present pattern linking neuroticism with less adaptive motivational functioning in online contexts (Quigley et al., 2022).

Our results are aligned with the broader literature linking conscientiousness positively, and negative emotionality/neuroticism negatively, to academic outcomes in higher education. Recent Frontiers syntheses and SEM studies indicate that conscientiousness is among the most consistent Big Five traits associated with achievement and is often linked to academic outcomes through proximal motivational beliefs (e.g., self-efficacy), rather than showing uniformly strong direct associations with grades or motivation. This is consistent with recent SEM evidence indicating that the association between Big Five traits and academic outcomes is frequently indirect and operates through proximal motivational beliefs such as self-efficacy and identity-related mechanisms (Wang et al., 2023). We observed the same pattern: once peer-to-peer confirmation was modeled, the direct personality trait to learning motivating factors path diminished, suggesting that personality-related advantages may translate into motivation primarily when peer processes are supportive. This is consistent with evidence that conscientiousness (and, in some cases, extraversion) influences achievement indirectly via self-efficacy chains, while neuroticism undermines these pathways (Li et al., 2024; Wang et al., 2023).

5.2 Peer-to-peer confirmation as a key mediator

Our results also extend previous work on social support by focusing on the specific construct of student-to-student confirmation, which includes individual attention, acknowledgment, and assistance (LaBelle & Johnson, 2018). This framing is supported by a recent review synthesizing student-to-student confirmation research and providing recommendations for its use in higher-education contexts (Johnson and LaBelle, 2024). This construct operationalizes the peer-based relatedness need described in SDT and aligns with evidence that peer support is linked to self-regulated learning and engagement in higher education (Martínez-López et al., 2023).

In the present study, peer-to-peer confirmation was the most consistent mediator, linking personality traits with e-learning motivating factors. Once peer-to-peer confirmation was included, the direct path from personality traits to e-learning motivation became non-significant, consistent with an indirect pathway via peer-to-peer confirmation in this specification. This pattern is consistent with an indirect pathway via peer-to-peer confirmation, tested using bias-corrected bootstrapping. These findings suggest that personality traits, higher conscientiousness and lower neuroticism, may translate into stronger e-learning motivation primarily when learners experience affirming

peer interactions and communications—attention, acknowledgement, and assistance—supporting belonging and engagement in e-learning (Johnson and LaBelle, 2024; Kerimoğlu et al., 2023) and aligning with SDT's proposition that relatedness is central to sustaining intrinsic motivation (Ryan and Deci, 2000). It also aligns with findings that social support shows a robust positive associatons with e-learning motivation (Berestova et al., 2022; Yang et al., 2025). This interpretation also aligns with broader findings that social support is positively associated with motivation and engagement in e-learning contexts (Berestova et al., 2022; Yang et al., 2025; Hu and Xiao, 2025).

Importantly, recent evidence from digital "Study With Me" learning practices further supports the motivational relevance of peer processes: peer support in online study communities has been linked to learning outcomes through motivational and anxiety-related pathways (Hou et al., 2025). More broadly, research in educational communication indicates that confirmation is a meaningful motivational construct; the present study extends this logic by demonstrating an analogous confirmation process among peers in e-learning contexts (Gao, 2021).

Finally, although prior studies have reported stronger direct associations between mental health indicators and e-learning outcomes (Dirzyte et al., 2021a; Paechter et al., 2022; Fu et al., 2024), the present integrated model suggests that peer-to-peer confirmation may account for motivationally relevant variance that could otherwise be attributed to distress in simpler (bivariate) models. Differences in measurement scope (e.g., clinical symptom severity vs. subclinical distress), sample characteristics, and contextual factors may also contribute to variability across studies.

5.3 The limited mediating role of mental health

Although personality traits—latent factor defined by conscientiousness and neuroticism in the final integrated SEM model was strongly associated with mental health indicators, the direct association of anxiety and depression symptoms with learning motivating factors in e-learning was not statistically significant once peer-to-peer confirmation was included, nor did mental health an indirect pathway from personality traits to learning motivating factors in e-learning context. While some studies have reported negative associations between mental health indicators and on e-learning outcomes (Dirzyte et al., 2021a; Fu et al., 2024; Paechter et al., 2022), the present findings are more consistent with a buffering hypothesis: supportive peer communication may reduce the academic salience of psychological distress (LaBelle and Johnson, 2021). More broadly, recent psychosocial mediation evidence in student populations illustrates that anxiety-related outcomes can be explained by specific proximal mechanisms (e.g., self-acceptance), supporting the interpretation that distress indicators may not operate as a dominant explanatory pathway once interpersonal processes are modeled (Chen and Lai, 2025). For example, Paechter et al. (2022) showed that learning with anxiety and maladaptive cognitions can impair learning in adverse circumstances, while self-concept and motivation may be protective, which aligns with our interpretation that more proximal motivational and interpersonal factors may shape the role of distress in e-learning. Moreover, confirmation among peers has been linked to student mental health and well-being, which is relevant to our interpretation that peer processes may account for variance otherwise attributed to distress indicators in bivariate associations (LaBelle and Johnson, 2021). This interpretation is also consistent with that supportive social climates may buffer the motivational correlates of distress in e-learning (Hu and Xiao, 2025). A measurement explanation is also plausible: GAD-7 and PHQ-9 primarily capture clinical symptom severity, whereas subclinical or situational distress—potentially more relevant for day-to-day academic motivation—was not directly assessed. Additionally, cultural or contextual factors (e.g., Lithuanian higher-education settings and the specific e-learning environments sampled) may have contributed to the observed pattern.

5.4 Practical implications

Our study findings have clear implications for e-learning design and student support strategies. First, we suggest that online courses should intentionally scaffold peer-to-peer confirmation. Foster peer-to-peer confirmation through collaborative task, peer mentoring, rubric-guided peer feedback, and structured discussion forums that prompt acknowledgment and micro-assistance. Second, instructors should be supported and trained not only in content facilitation, but also in seeding and maintaining supportive peer interactions, for example by modeling confirming language, setting norms for constructive interaction, and designing activities that require reciprocal support. Third, although mental health was not directly related e-learning motivation in the integrated model, the strong association with personality traits and peer processes indicates the need for preventive and responsive student services (Lin et al., 2025). Such supports may include low-threshold well-being check-ins embedded in group projects, flexible pacing where feasible, and periodic instructor outreach for students at risk. From a practical standpoint, these findings suggest that fostering peer-to-peer confirmation should be a deliberate goal in online course design. Finally, these findings align with prior work (Capon-Sieber et al., 2022; Yang et al., 2025; Hu and Xiao, 2025), suggesting that relatedness-supportive practices and peer/teacher social support promote engagement and self-regulated learning online. As Yang et al. (2025) suggested, practical strategies to foster peer-to-peer confirmation include "engaging in online learning communities, exchanging experiences with other peers, sharing learning resources, and organizing online learning groups for mutual support and encouragement." Future interventions could combine mental health resources with peer-to-peer activities, such as embedding well-being check-ins within group projects. From a practical standpoint, this means that interventions such as structured peer feedback, small-group collaborative projects, or integrated peer review systems in LMS platforms (e.g., Moodle, Canvas) may be particularly effective for enhancing motivation.

5.5 Limitations and future directions

Several limitations should be acknowledged. First, the cross-sectional design limits causal inference and precludes conclusions about regarding temporal ordering. All measures were self-reported, which may increase common-method variance and response biases (e.g., social desirability). Moreover, reverse directionality also remains possible; for example, learners with higher motivation may be more likely engage in peer interaction or to perceive higher levels of peer-to-peer confirmation. Accordingly, the indirect associations estimated in the SEM should be interpreted as statistical indirect associations, not causal mediation. Future research should use longitudinal and/or experimental designs to test temporal precedence and evaluate whether enhancing peer-to-peer confirmation prospectively increases

motivation, and whether such effects are stronger for student's lower in conscientiousness or higher in neuroticism.

Second, our sample included Lithuanian university students and learners from specific e-learning contexts with voluntary participation, which may limit the external validity, generalizability of findings to other cultural or institutional contexts. Basic demographic and academic background characteristics are reported in Supplementary Table; however, more detailed socioeconomic or cultural variables (e.g., income, parental education, and ethnicity) were not assessed, limiting our ability to test potential confounding or moderation by these factors.

Third, although all instruments were translated and back-translated into Lithuanian using standard procedures, the study did not include full stand-alone validation studies or measurement invariance testing. For PHQ-9 and GAD-7, later Lithuanian research supports their factor structure and screening performance (Pranckeviciene et al., 2022; Stanyte et al., 2023), partly mitigating this concern. For learning motivation, student-to-student confirmation, and personality traits, evidence is limited to the CFAs and reliability estimates reported here, so future studies should provide dedicated validation and invariance analyses in Lithuanian e-learning samples.

Fourth, although the indirect pathway via mental health was not supported in the final integrated model, mental health indicators remained strongly associated with personality-related variance and peer-to-peer confirmation, suggesting potential temporal or contextual dependencies not captured in the cross-sectional specification. Future studies should examine whether peer-related social processes buffer the distress–motivation association over time, using longitudinal designs and more fine-grained measures of situational academic distress alongside symptom severity.

6 Conclusion

This study examined associations among personality traits, mental health indicators (anxiety and depression), peer-to-peer confirmation, and learning motivating factors in e-learning within an SDT-informed structural model. The findings provide empirical evidence that peer-to-peer confirmation is the central pathway linking personality traits to learning motivating factors in the tested model. Specifically, peer-to-peer confirmation showed a direct positive association with e-learning motivating factors and supported an indirect pathway between personality traits and e-learning motivating factors via peer-to-peer confirmation, whereas the indirect pathway via mental health was not supported in the final integrated model.

From an applied perspective, the results indicate that motivation-supportive e-learning design should include structured opportunities for peer acknowledgement, assistance, and individual attention. By embedding opportunities for acknowledgement, assistance, and individual attention within online courses, educators may strengthen learners' sense of relatedness, which is theoretically consistent with SDT and empirically supported by the present model.

Given the cross-sectional design, the reported relations should be interpreted as associations rather than causal effects. Future research should test these pathways using longitudinal or experimental designs and evaluate whether interventions that strengthen peer-to-peer confirmation prospectively improve e-learning motivation.

What this study adds

This study makes several novel contributions to the literature on e-learning motivation. First, it brings together personality traits, mental health indicators, and peer-to-peer confirmation within a single SDT-informed structural (associational) framework, allowing these constructs to be examined concurrently rather than in isolation. Second, by comparing two SEM models, the findings emphasize an indirect pathway in which personality-related differences are linked to e-learning motivating factors, primarily through peer-to-peer confirmation, rather than through a direct personality-motivation association. Third, by conceptualizing peer-to-peer confirmation, capturing individual attention, acknowledgement, and assistance, this study offers a more fine-grained account of how specific affirming peer interactions relate to motivation in e-learning, beyond generic "social support" measures. Finally, although personality traits are strongly associated with mental health indicators, mental health did not emerge as a key explanatory pathway for motivation once peer-to-peer confirmation was considered, suggesting that peer-related social processes may be particularly salient for understanding motivational differences in the e-learning context.

Impact statement

This study advances understanding of e-learning motivation by integrating personality traits, mental health, and peer-to-peer confirmation into a single structural equation model. Findings highlight that peer interactions, rather than direct associations of personality traits or mental health, are most strongly associated with e-learning motivating factors.

Data availability statement

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

Ethics statement

Ethical approval for the study was granted by the Institutional Review Board of Klaipeda University (Approval No. STIMC—BMTEK-P03, April 12, 2021). 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: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. AD: Conceptualization, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

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Correction note

This article has been corrected with minor changes. These changes do not impact the scientific content of the article.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2026.1706979/full#supplementary-material

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