Article

Peer-to-Peer Confirmation, Positive Automatic Thoughts, and Flourishing of Computer Programming E-Learners

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Abstract: Computer programming e-learners faced stressful life circumstances and educational changes that affected the world during the COVID-19 pandemic. As the cognitive model of flourishing focuses on cognitions rather than situations themselves, it was deemed significant to identify peer-to-peer confirmation, positive automatic thoughts, flourishing, and the links between these study variables in a group of computer programming e-learners and compare the results with other e-learners. This study applied the Flourishing Scale (FS), the Automatic Thoughts Questionnaire—Positive (ATQP), and the Student-to-Student Confirmation Scale. The sample consisted of 453 e-learners, including 211 computer programming e-learners. The results revealed that computer programming e-learners differed from other e-learners in flourishing, positive daily functioning, and peer-to-peer confirmation. In both samples, positive daily functioning and positive future expectations predicted self-reported flourishing. Positive automatic thoughts and flourishing predicted peer-to-peer confirmation just in the group of computer programming e-learners. The SEM analysis revealed that peer-to-peer confirmation and positive automatic thoughts explained 57.4% of the variance of flourishing in the computer programming e-learners group and 9.3% of the variance in the social sciences e-learners group, $\chi^2 = 81.320$, $df = 36$, $p < 0.001$; NFI = 0.963; TLI = 0.967; CFI = 0.979; RMSEA = 0.075 [0.053–0.096]; SRMR = 0.033. The findings signify the importance of peer-to-peer confirmation and positive thoughts for computer programming e-learners' psychological well-being. Nevertheless, the results of this particular study should be regarded with caution due to the relatively small sample size and other limitations. In the future, it would be valuable to identify the underlying mechanisms and the added value of positive states such as flow, which have recently received the increased attention of researchers.

Keywords: peer-to-peer confirmation; positive automatic thoughts; flourishing; computer programming; e-learning

1. Introduction

Computer programming education faced difficulties that affected the world during the COVID-19 pandemic [1]. The preliminary research on the costs of the coronavirus outbreak on mental health reveals a statistically significant increase in the rates of unsatisfactory psychological well-being [2], anxiety [3], stress [4–6], and burnout [7].

Furthermore, many countries worldwide face the need for rapid implementation of e-learning. As Bond et al. [8] point out, “the COVID-19 pandemic led to the unprecedented

situation of having to switch to online instruction, with considerable impact on students in all levels of education” [8].

Research indicates that in the times of the COVID-19 quarantine some university students develop emotional difficulties due to stressful life circumstances [9], which may affect satisfaction with e-learning [10] or might lead to diminished e-learning motivation or even absence of it [11].

Even though some studies demonstrated the negative impact of changed conditions, the cognitive model of emotional difficulties refers not to life circumstances itself [12], but cognitive processes or, at least, interactions between situations and cognitions [13–15]. Biased information processing and cognitive specificity of misleading beliefs play a central role in triggering emotional difficulties [16]. On the other hand, positive automatic thoughts promote psychological well-being [17] and result in the absence of depression [18]. These effects are very important for education, as depression increases the rates of dropout and lowers educational attainments [19–22], while flourishing is linked to many positive educational outcomes [23,24].

This study explores the role of cognitive specificity of beliefs and psychological flourishing in e-learning based education. As the student-centered approach delineates the importance of peer-to-peer confirmation in education, this study also aimed to identify associations between positive thoughts, flourishing, and peer-to-peer confirmation.

1.1. Student-Centered Approach and Peer-to-Peer Confirmation

A student-centred approach as a keystone of education has been researched for several decades [25–27], revealing new roles of educators and learners. The student-centred approach has brought more emphasis on learners’ activity and their responsibility for the learning outcomes, while the teacher’s role switched to facilitating and fostering students’ discovery, collaboration, cooperation, and engagement in constructing new knowledge [27].

Having moved to e-learning, a great shift in education in terms of a student-centred approach has been witnessed as the new roles had to be reconsidered [28]. Constructs, such as student support [28,29], peer-to-peer relationship, connectedness, or instructional dissent [30–33] have been widely explored. These investigations led to new areas of research to what extent students influence each other in educational settings. Johnson and LaBelle [34,35] defines such student-centric construct in the instructional environment as “student-to-student confirmation” [34,35].

The concept of “confirmation” in the academic environment has been analysed from two perspectives: teachers’ confirming messages and students’ communicative behaviours [36]. “Confirmation” stipulates a wish not only to interact with another individual but also to engage in a relationship with another person [37]. Recently, confirmation has been widely researched in educational settings [34,38], emphasizing the impact of confirmation by both teachers and peers revealing positive perceptions and learning outcomes for students [35,38].

The impact of teacher confirmation has been analysed through four dimensions: responding to students, demonstrating interest in student learning, teaching style, and the absence of disconfirmation [38]. Research revealed that teacher confirmation directly influences students’ communicative behaviours [39].

A study conducted by Goodboy and Myers [39] showed that teacher confirmation has a constructive impact on students’ active participation, cognitive and affective learning, motivation, and satisfaction [39]. Other studies revealed that students, who receive confirming messages from peers, report greater affective learning, motivation, and engagement [34,35].

A study conducted by Sidelinger and Booth-Butterfield [32] revealed that “peer-to-peer connectedness mediated the relationships between teacher confirmation behaviours and in-class student involvement”, which also proved that peer-to-peer connectedness is an important predictor of student involvement and a classroom resource [32].

Peer-to-peer confirmation is “the transactional process by which students communicate that they endorse, recognize, and acknowledge their peers as valuable and significant

individuals" [34,35]. Johnson and LaBelle's [34] research reveals that students declare their peers of great value and significance in terms of three dimensions of peer-to-peer confirmation: acknowledgement, assistance, and individual attention. Acknowledgement is viewed as peers' confirmation of performance level, knowledge or developed and demonstrated skills in a course. Peer-to-peer confirmation via assistance is described as an act of giving or receiving help in the educational setting [34,35]. Individual attention is considered peers' support, encouragement or expressed interest in another individual's well-being [34].

Peer-to-peer confirmation has been analyzed in relation to their engagement in the course, which happens both inside and outside the classroom [40,41]. The research results disclosed the connection between student confirmation and out of class behaviours, such as discussing course content and studying with peers. All three dimensions of peer-to-peer confirmation (acknowledgement, assistance, and individual attention) demonstrated a significant positive relationship with the oral in-class behaviours, thinking about course content, and out of class behaviours of student engagement, but were not related to silent in class behaviours [41].

In summary, previous research suggested several positive factors related to peer-to-peer confirmation, but these results were based on face-to-face teaching and learning, inside and outside classroom interactions. An exploration of peer-to-peer confirmation in a distant learning environment might provide supplemental information on the contributing factors.

1.2. Psychological Flourishing

Psychological flourishing is a concept that encompasses some of the well-being (subjective, psychological, social, emotional) components [42,43], is synonymous with a high level of psychological well-being [42], and is linked to mental health [44–46]. Flourishing is characterized as individuals' evaluations of how well they feel they are functioning in their lives [44]. Literature suggests several theoretical conceptualizations of flourishing:

According to Diener et al. [42], flourishing incorporates purpose and meaning in life, positive relationships, engagement, competence, self-acceptance and self-esteem, optimism, and social contribution towards the well-being of others [42].

Hupert and So [47] identify ten features of positive well-being: positive feeling and positive functioning, i.e., hedonic, and eudemonic aspects of well-being: competence, emotional stability, engagement, meaning, optimism, positive emotion, positive relationships, resilience, self-esteem, and vitality [47].

Keyes' [48] theoretical model of flourishing consists of positive relationship, positive affect (interest), purpose in life, positive affect (happiness), social contribution, social integration, social growth, social acceptance, social coherence, environmental mastery, personal growth, autonomy, life satisfaction [48].

Seligman [49] describes flourishing by positive relationships, engagement, meaning and purpose, accomplishments/competence, and positive emotions [49].

Despite the lack of consensus on a theory, conceptualization, and definition of flourishing, there is substantial agreement in all operational definitions that flourishing is a combination of a set of hedonic and eudemonic indicators, with an overlap in the areas of (1) positive relationships, (2) positive affect and engagement, and (3) meaning and purpose [50,51]. "Positive relationships" delineates a person's perception to what extent he receives help and support from others when he needs it and to what extent the person has been feeling loved, or how much he is satisfied with personal relationships. "Engagement" outlines how much a person becomes absorbed in personal activities, to what extent he feels excited and interested in things. "Meaning and purpose" defines the extent a person perceives leading a purposeful and meaningful life, to what extent he recognizes personal activities as valuable and worthwhile, and has a sense of direction in his life [51].

Predictors of flourishing include academic achievement [23,24], supportive college environments, ease with transitioning, sense of belonging [52], volunteering, and service-learning [53]. On the other hand, students who have higher perceptions of 'social-psychological prosperity' that is characterized by greater competence, purpose in life, self-esteem, op-

timism, and harmonious relationships, report that they invest greater efforts in completing academic tasks and experience positive emotions when doing academic activities [54]. Furthermore, flourishing is positively linked to greater behavioural and emotional engagement in an educational context. Several studies reported similar results: well-being increases academic engagement [55], motivation [56], and it matters for successful learning [23,24].

Next, flourishing is related to various desired outcomes such as life satisfaction, physical and mental health [57], self-enhancement [58], positive emotions, and persistence in pursuing achievement goals orientation [54]. These parameters are essential for students' academic achievement, study involvement, dropout prevention, and successful careers. Goal orientation and self-enhancement lead to better academic achievement, and improved achievement lead to better academic self-concept and academic motivation [59].

In contrast to flourishing, life dissatisfaction is linked to low levels of health, higher levels of depression, personality problems, and health inappropriate behaviour [60], which negatively influences academic achievements and engagement. Research indicates that students struggling with mental illnesses are at greater risk of academic failure [61].

Furthermore, positively minded students are more active, tend to appreciate and support more often and more positively their peers, and vice versa, those who receive more and positive support achieve better results [55,62–65]. Therefore, parameters preconditioned by flourishing are essential to successful learning and are called 'the central purpose of education' [66] (p. 42).

1.3. Positive Automatic Thoughts

Automatic thoughts are the "stream of thoughts, ideas and images which constantly accompany an individual as he or she proceeds through daily life" [67] (p. 70). The importance of thought automaticity has been emphasized in modern cognitive theories. There is a distinction between fast, unconscious, automatic, and effortless thinking and slow, conscious, deliberate, and effortful thinking [68]. Conceptualizing specific thoughts as "automatic" means that these thoughts happen spontaneously, without determined intent or effort.

Wong [69] found that negative automatic thoughts were inversely correlated with life satisfaction and happiness and concluded that a higher ratio of positive automatic thoughts to the sum of positive and negative automatic thoughts led to better mental health outcomes [69]. A person's negative automatic thoughts about the self and the world, supported by their intermediate and core beliefs, set up a self-reinforcing cycle that predisposes an individual to emotional deregulation and maladaptive behaviour [16].

Research also proposed, however, that positive automatic thoughts play a role in overall psychological functioning. For instance, Ingram and Wisnicki [17] identified cognitive dimensions associated with good moods and positive experiences: positive daily functioning, positive self-evaluation, others' evaluations of the self, and positive future expectations. Empirical evidence supports that positive automatic thoughts are linked to psychological health and the absence of depression. Of course, the absence of depression does not necessarily correspond to exceptional psychological well-being. Studies focusing only on negative mood states may not shed light on the nature and correlates of positive functioning [18]. However, many studies confirm that depression substantially reduces physical, social, and cognitive functioning, is a cause of dropouts, and lowers educational attainments [19–22]. All these aspects are fundamental in autonomous e-learning as the learners have to deal with the challenges independently. The decision to finish an e-learning course requires motivation, everyday efforts, high self-esteem [23,24,55,56].

Research suggests that e-learning meets many challenges; therefore, an analysis of contributing factors might provide additional information on successful learning [70–73]. Moreover, there is a lack of empirical data on the links between automatic thoughts, peer-to-peer confirmation, and flourishing, especially, in the context of e-learning. Consequently, the purpose of this study was to explore the links between positive automatic thoughts, flourishing, and peer-to-peer confirmation in e-learning based education.

This study targeted students enrolled in e-learning-based computer programming education because computer programming is one of the most challenging learning tasks [74], demonstrating the highest rates of learning failures [75]. Moreover, learners worldwide are encouraged to attain computer programming skills [76], though acquiring computer programming skills might be extremely challenging for some learners [77].

In this survey, we have chosen to analyze two samples: those who participate in e-learning-based computer learning courses and those who study social sciences in various university programs, but they are studying remotely due to the COVID-19 pandemic.

Even though studies are suggesting that computer programming learners differ from other learners in their personality traits, namely, lower extraversion [78], which implies possible differences in peer-to-peer confirmation skills, but research indicates no significant dissimilarities in psychological flourishing or positive thinking of learners. Thus, it is unclear whether computer programming learners are better at peer-to-peer confirmation, and whether the associations between positive automatic thoughts, flourishing, and peer-to-peer confirmation differ between participants and non-participants of e-learning based computer programming courses.

In summary, computer programming e-learners faced stressful life conditions that affected the world during the COVID-19 pandemic. As the cognitive model of flourishing suggests that cognitions rather than conditions determine psychological wellbeing and perceptual outcomes, it was considered significant to explore the links between positive automatic thoughts, flourishing, and peer-to-peer confirmation, and compare these links in groups of computer programming and other e-learners. This study is the first which investigates the links between positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation in e-learning-based education, including computer programming learning. Most of the previous studies targeted the links between peer-to-peer confirmation and mental health [30,34,35,79], learning motivation and mental health indicators, such as depression and anxiety [1,34,35], with a narrow focus on psychological wellbeing [79]. This study primarily targeted the positive psychology construct of flourishing and positive automatic thoughts in relation to peer-to-peer confirmation in e-learning. The context of the COVID-19 quarantine, which brought the rapid implementation of e-learning [80], facilitated the comparison of associations between the study variables in different samples.

This study attempted to answer research question whether peer-to-peer confirmation, positive automatic thoughts, flourishing and the links between them differ in groups of computer programming and other e-learners. Thus the goal of this study was to identify peer-to-peer confirmation, positive automatic thoughts, flourishing, and the links between these study variables in a group of computer programming e-learners and compare the results with other e-learners.

Based on previous research, we hypothesized that:

Hypothesis 1 (H1). *Computer programming e-learners do not differ in their positive automatic thoughts and self-reported flourishing from other e-learners;*

Hypothesis 2 (H2). *Computer programming e-learners differ in their peer-to-peer confirmation from other e-learners;*

Hypothesis 3 (H3). *Positive automatic thoughts predict self-reported flourishing in both groups of participants and non-participants of e-learning based computer programming courses;*

Hypothesis 4 (H4). *Self-reported flourishing and positive automatic thoughts predict peer-to-peer confirmation of participants and non-participants of e-learning based computer programming courses;*

Hypothesis 5 (H5). *Associations between self-reported flourishing, positive automatic thoughts and peer-to-peer confirmation differ between participants and non-participants of e-learning based computer programming courses.*

2. Materials and Methods

2.1. Sample

In the full sample of 453 participants, a total of 453 participants had no missing data. The study's subjects included 32.7 percent of males ($N = 148$) and 67.3 percent of females ($N = 305$). The respondents' mean age was 26.10 years ($SD = 8.363$, 95% CI = 25.33, 26.88, age range = from 18 to 56 years). 242 (53.4%) of participants studied in e-learning based computer programming courses organized by Turing College. The comparative group consisted of 211 (46.6%) respondents who studied social sciences at various Lithuanian universities, but were studying remotely due to the COVID-19 pandemics.

At the time of the research, both groups of e-learners (computer programming and social sciences) were undertaking their studies. E-learners were informed about the study by e-mail and provided their consent to participate in the research. Participation in the study was voluntary, and the participants did not receive any compensation. The procedure was administered online at <https://www.psytest.online> (accessed on 8 August 2021) and followed the General Data Protection Regulation (GDPR) guidelines and the Declaration of Helsinki. The study was approved by the Institutional Review Board of the Institute of Management and Psychology.

2.2. Instruments

This study applied three instruments, the Lithuanian translated version of the Flourishing Scale (FS) [42], the Lithuanian translated version of the Automatic Thoughts Questionnaire—Positive (ATQP) [17], the Lithuanian translated version of the Student-to-Student Confirmation Scale, [35]. To ensure that the Lithuanian items corresponded as closely as possible to the English items, the original items of both instruments were translated into Lithuanian and back-translated.

2.2.1. The Flourishing Scale

To assess psychological flourishing, we applied the Flourishing Scale (FS) of Ed Diener and colleagues consisting of 8 items [42]. The Flourishing Scale measures the respondent's self-perceived success in important areas such as relationships, self-esteem, purpose, and optimism. The scale provides a single psychological well-being score. In our study, the response pattern followed a 5-point Likert scale ranging from 5 (totally agree) to 1 (totally disagree). The Flourishing Scale over the last decade has been validated across several populations (e.g., post-secondary students) [58,81–83], older adults [84]. Validation studies confirmed the one-dimensional structure of the FS, evidencing the instrument's internal consistency [42].

2.2.2. The Automatic Thoughts Questionnaire—Positive

We applied the Automatic Thoughts Questionnaire—Positive (ATQP) [17] to assess positive automatic thoughts. The ATQP, a 30-item self-report instrument, measures positive automatic thoughts. Items consist of statements representing positive automatic thoughts; respondents rated frequency of positive automatic thoughts on a 5-point Likert scale ranging from 1 (Not at all) to 5 (All the time). Item ratings are summed to produce a total score. Previous research validated the four-dimensional structure and internal consistency of the positive automatic thoughts' questionnaire [17].

2.2.3. The Student-to-Student Confirmation Scale

To assess peer-to-peer confirmation, we applied the Student-to-Student Confirmation Scale, developed by LaBelle and Johnson [35]. This 25-items scale assesses student's experience receiving confirmation from peers along three dimensions: individual attention,

acknowledgment, and assistance. The individual attention dimension includes 10 items that assess participants' reception of confirming messages which let them know that they are significant as unique individuals. The acknowledgment dimension includes 9 items that assess participants' experience receiving messages that acknowledge their abilities related to academics and course content. The assistance dimension includes six items that assess participants' reception of confirmation from peers in the form of assistance or help. Participants were asked to respond on 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 [35].

In this study, for reliability and validity analysis, Cronbach's alpha, McDonald's omega, composite reliability (CR) and average variance extracted (AVE) indexes were calculated. Microsoft Excel software was used to calculate composite variability and average variance extracted, which are indicators of convergent validity. The average variance extracted should be higher than the minimum threshold of 0.5. However, according to Fornell and Larcker, even if AVE is less than 0.5, but CR is higher than 0.6, the convergent validity of the construct is still adequate [85].

Cronbach alpha, McDonald's omega, composite reliability and average variance extracted indexes for the used instruments the Flourishing Scale (FS), the Automatic Thoughts Questionnaire—Positive (ATQP), and the Student-to-Student confirmation scale in this research are presented in Table 1.

Table 1. Cronbach alphas for the Flourishing Scale (FS), the Automatic Thoughts Questionnaire—Positive (ATQP), and the Student-to-Student confirmation scale.

Scales and Subscales	Cronbach Alpha	McDonald's Omega	CR	AVE
Automatic Thoughts Questionnaire—Positive (ATQP)	0.966	0.966	0.966	0.492
Positive daily functioning subscale	0.934	0.935	0.935	0.592
Positive self-evaluation subscale	0.870	0.872	0.872	0.534
Other evaluation of self subscale	0.809	0.814	0.810	0.520
Positive future expectation subscale	0.917	0.917	0.917	0.847
Flourishing Scale (FS)	0.859	0.860	0.860	0.438
Student-to-Student Confirmation Scale	0.967	0.968	0.979	0.696
Individual attention subscale	0.957	0.958	0.958	0.698
Acknowledgement subscale	0.949	0.950	0.949	0.676
Assistance subscale	0.940	0.940	0.939	0.722

CR, composite reliability; AVE, average variance extracted.

2.3. Statistical Analysis

For data analysis, we used SPSS v.26.0 (IBM Corp., Armonk, NY, USA). The structural equation modeling (SEM) was conducted using AMOS v.26.0 (IBM Corp., Armonk, NY, USA) and JASP v. 0.14.1.0 (University of Amsterdam, Amsterdam, The Netherlands).

Applying the SEM methodology is beneficial as it tests whether the theoretical structural relationships between the constructs are meaningful and significant [86–98]. Research suggests that several SEM methodologies can be applied for the data analysis: partial least squares structural equation modeling (PLS-SEM), and covariance-based structural equation modeling (CB-SEM). PLS-SEM is not based on covariances and thus does not have a fit measure, and CB-SEM is based on covariances and requires fit, and is assessed on the basis of reliability, convergent validity, and discriminant validity, as well as on how well the relationships between the indicator variables can be reproduced [92,94]. PLS-SEM methodology is best for applying when the research objective is exploratory,

focused on prediction or explaining the relationships between exogenous and endogenous constructs, when the sample size is small ($n < 100$), the measurement models are complex (6 and more constructs and more than 50 indicators), the scaling of responses is ordinal or nominal, the data is secondary/archival, particularly single-item measures. In PLS-SEM, the research objective is to use latent variable scores in subsequent analyses, the structural model is estimated with a higher-order construct that has only two first-order constructs, the analysis involves a continuous moderator, the investigation examines the model for unobserved heterogeneity, and the data are not normally distributed [88,92,94]. Even though this study and the data met some of the rules of thumb for choosing the PLS-SEM (lacks solid theoretical foundation, the data were not normally distributed, etc.) and we measured several second-order constructs (peer-to-peer confirmation, positive automatic thoughts), but the data also met some of the main rules of thumb for choosing the CB-SEM. Thus we have applied the CB-SEM methodology, which is usually preferred when the research objective is confirmation of well-developed structural and measurement theory based on common variance, the measurement philosophy is estimation with the common factor model using only common variance (covariances), the research requires a global goodness-of-fit criterion, the error terms require additional specification, such as covariation, the structural model specifies non-recursive relationships or the measurement models are simple (5 or fewer constructs and 50 or fewer indicators) [92,94].

In this study, model fit was evaluated based on the CFI (Comparative Fit Index), the Normed Fit Index (NFI), the Tucker–Lewis coefficient (TLI), RMSEA (Root Mean Square Error of Approximation), and SRMR (Standardized Root Mean Square Residual), whereas the χ^2 was used for descriptive purposes only because it is highly sensitive to sample size [99]. The values higher than 0.90 for CFI, NFI, and TLI, and values lower than 0.08 for RMSEA and SRMR, were considered as indicative of a good fit [100]. We considered p -values less than 0.05 to be statistically significant [101].

The Shapiro–Wilk test showed the departure from normality for the variables of positive daily functioning $W(453) = 0.986, p < 0.001$; positive self-evaluation $W(453) = 0.983, p < 0.001$; other evaluation of self $W(453) = 0.978, p < 0.001$; positive future expectation $W(453) = 0.939, p < 0.001$; flourishing $W(453) = 0.977, p < 0.001$; individual attention $W(453) = 0.952, p < 0.001$; acknowledgement $W(453) = 0.954, p < 0.001$; assistance $W(453) = 0.951, p < 0.001$.

Similarly, the Kolmogorov–Smirnov test showed that data were non-normally distributed for the variables of positive daily functioning $D(453) = 0.057, p = 0.001$; positive self-evaluation $D(453) = 0.073, p < 0.001$; other evaluation of self $D(453) = 0.110, p < 0.001$; positive future expectation $D(453) = 0.159, p < 0.001$; flourishing $D(453) = 0.084, p < 0.001$; individual attention $D(453) = 0.081, p < 0.001$; acknowledgement $D(453) = 0.159, p < 0.001$; assistance $D(453) = 0.110, p < 0.001$.

The distribution was moderately skewed: positive daily functioning skewness = -0.116 ($SE = 0.115$), kurtosis = -0.683 ($SE = 0.229$); positive self-evaluation skewness = -0.279 ($SE = 0.115$), kurtosis = -0.294 ($SE = 0.229$); other evaluation of self skewness = -0.270 ($SE = 0.115$), kurtosis = -0.460 ($SE = 0.229$); positive future expectation skewness = -0.396 ($SE = 0.115$), kurtosis = -0.376 ($SE = 0.229$); flourishing skewness = -0.435 ($SE = 0.115$), kurtosis = -0.199 ($SE = 0.229$); individual attention skewness = -0.685 ($SE = 0.115$), kurtosis = 0.849 ($SE = 0.229$); acknowledgement skewness = -0.484 ($SE = 0.115$), kurtosis = 0.828 ($SE = 0.229$); assistance skewness = -0.635 ($SE = 0.115$), kurtosis = 0.726 ($SE = 0.229$).

3. Results

The means, standard deviations, and correlations between the Automatic Thoughts Questionnaire—Positive (ATQP) subscales in this study are reported in Table 2.

Table 2. The Automatic Thoughts Questionnaire—Positive (ATQP) subscales: descriptive statistics and correlations between the subscales.

The ATQP Variables	<i>M</i>	<i>SD</i>	1	2	3
Positive daily functioning	3.016	0.922	-		
Positive self-evaluation	3.095	0.912	0.816 ***	-	
Other evaluation of self	3.177	0.876	0.761 ***	0.715 ***	-
Positive future expectation	3.243	1.034	0.710 ***	0.703 ***	0.620 ***

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

The means, standard deviations, and correlations between the Student-to-Student Confirmation Scale's subscales in this study are reported in Table 3.

Table 3. The Student-to-Student Confirmation Scale's subscales: descriptive statistics and correlations between the subscales.

The Student-to-Student Confirmation Scale Variables	<i>M</i>	<i>SD</i>	1	2
Individual attention	3.660	0.837	-	
Acknowledgement	3.255	0.836	0.668 ***	-
Assistance	3.522	0.856	0.688 ***	0.557 ***

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

The means, standard deviations, and correlations between the Student-to-Student Confirmation Scale's, Positive Automatic Thoughts scale's and Flourishing scale's in this study are reported in Table 4.

Table 4. Descriptive statistics and correlations between the Automatic Thoughts Questionnaire—Positive (ATQP), Flourishing Scale (FS), and Student-to-Student confirmation questionnaire.

Variables	<i>M</i>	<i>SD</i>	1	2
Positive automatic thoughts (ATQP)	3.094	0.808	-	
Student-to-student confirmation	3.481	0.737	0.254 ***	-
Flourishing (FS)	3.782	0.667	0.543 ***	0.276 ***

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

To test H1, if computer programming e-learners do not differ in their positive automatic thoughts and self-reported flourishing from other e-learners, we have conducted the independent samples T-test. The results are displayed in Table 5.

Table 5. Comparison of positive automatic thoughts and self-reported flourishing between the groups of participants and non-participants of e-learning based computer programming courses.

	<i>t</i>	<i>df</i>	<i>p</i>	Mean Difference	SE Difference	Cohen's <i>d</i>	95% CI for Cohen's <i>d</i>	
							Lower	Upper
Positive automatic thoughts (ATQP)	−1.447	451	0.149	−0.110	0.076	−0.136	−0.321	0.049
Positive daily functioning	−2.331	451	0.020	−0.201	0.086	−0.220	−0.405	−0.034
Positive self-evaluation	−0.557	451	0.578	−0.048	0.086	−0.052	−0.237	0.132
Other evaluation of self	−1.493	451	0.133	−0.123	0.082	−0.141	−0.325	0.044
Positive future expectation	−1.209	451	0.277	−0.118	0.097	−0.114	−0.299	0.071
Flourishing (FS)	−2.965	451	0.003	−0.185	0.062	−0.279	−0.465	−0.094

T-test analysis has revealed some significant differences between groups: non-participants of computer programming e-learning courses demonstrated higher scores ($M = 3.124$, $SD = 0.892$) of positive daily functioning than participants of computer programming e-learning courses ($M = 2.922$, $SD = 0.939$), $p = 0.020$. Surprisingly, non-participants of computer programming e-learning courses demonstrated higher scores ($M = 3.880$, $SD = 0.613$) of flourishing than computer programming e-learning courses ($M = 3.696$, $SD = 0.700$), $p = 0.003$. No significant differences between the groups were found in positive automatic thoughts, positive self-evaluation, other self-evaluation, and positive future expectations.

Furthermore, to test H2, which presumed that computer programming e-learners differ in their peer-to-peer confirmation from other e-learners, we have also conducted the independent samples' T-test (Table 6).

Table 6. Comparison of student-to-student confirmation between the groups of participants and non-participants of e-learning based computer programming courses.

	t	df	p	Mean Difference	SE Difference	Cohen's d	95% CI for Cohen's d	
							Lower	Upper
Student-to-Student Confirmation	−3.614	451	<0.001	−0.247	0.068	−0.340	−0.526	−0.154
Individual attention	−3.302	451	0.001	−0.257	0.078	−0.311	−0.497	−0.125
Acknowledgement	−2.304	451	0.022	−0.181	0.078	−0.217	−0.402	−0.032
Assistance	−4.181	451	<0.001	−0.331	0.079	−0.394	−0.580	−0.207

T-test analysis revealed some statistically significant differences between the groups. Non-participants of computer programming e-learning courses demonstrated higher scores ($M = 3.613$, $SD = 0.745$) of a student-to-student confirmation than participants of computer programming e-learning courses ($M = 3.366$, $SD = 0.711$), $p < 0.001$. University students in social sciences demonstrated higher scores ($M = 3.797$, $SD = 0.811$) of individual attention than participants of e-learning based computer programming education ($M = 3.540$, $SD = 0.842$), $p = 0.001$. In addition, non-participants demonstrated higher scores ($M = 3.352$, $SD = 0.836$) of acknowledgement than computer programming e-learners ($M = 3.171$, $SD = 0.828$), $p = 0.022$. Moreover, non-participants of e-learning based computer programming education demonstrated higher scores ($M = 3.699$, $SD = 0.839$) of assistance in comparison to participants ($M = 3.368$, $SD = 0.843$), $p < 0.001$.

To test H3, assuming that positive automatic thoughts predict self-reported flourishing in both groups of participants and non-participants of e-learning based computer programming courses, we conducted multiple linear regression analyses. The results are displayed in Table 7.

Table 7. Multiple regression models, the dependent variable is flourishing, and the predictors are positive automatic thoughts.

Model	Non-Standardized Coefficients		Standardized Coefficients	t	Significance
	B	Standard Error	Beta		
A. Respondents do not participate in e-learning-based computer programming courses					
(Constant)	3.242	0.172		18.807	<0.001
Positive daily functioning	0.239	0.086	0.348	2.772	0.006
Positive self-evaluation	−0.077	0.085	−0.112	−0.904	0.367
Other evaluation of self	−0.079	0.078	−0.106	−1.017	0.310
Positive future expectation	0.118	0.059	0.187	2.000	0.047
R = 0.332; R Square = 0.110; Adjusted R Square = 0.093; Standard Error of the Estimate = 0.58341; F (4, 206) = 6.394, $p < 0.001$					

Table 7. Cont.

Model	Non-Standardized Coefficients		Standardized Coefficients	<i>t</i>	Significance
	<i>B</i>	Standard Error	Beta		
B. Respondents participate in e-learning-based computer programming courses (Constant)	2.015	0.112		18.068	<0.001
Positive daily functioning	0.354	0.066	0.475	5.396	<0.001
Positive self-evaluation	−0.042	0.059	−0.056	−0.718	0.474
Other evaluation of self	−0.025	0.052	−0.033	−0.488	0.626
Positive future expectation	0.268	0.043	0.414	6.240	<0.001
<i>R</i> = 0.762; <i>R</i> Square = 0.581; Adjusted <i>R</i> Square = 0.574; Standard Error of the Estimate = 0.45708; <i>F</i> (4, 237) = 82.125, <i>p</i> < 0.001					

A multiple regression model was calculated to predict flourishing based on positive automatic thoughts in groups of respondents participating and not participating in e-learning-based computer programming courses. A significant regression equation was found in the group of respondents participating in computer programming courses, $F(4, 237) = 82.125, p < 0.001$, with an $R^2 = 0.581$. Respondents' predicted flourishing was equal to $2.015 + 0.354$ (positive daily functioning) + 0.268 (positive future expectation) points. Flourishing increased 0.354 points for each positive daily functioning point and 0.268 points for each positive future expectation point. Positive daily functioning ($B = 0.354, p < 0.001$) and positive future expectation ($B = 0.268, p < 0.001$) contributed significantly to the model and were significant predictors of flourishing in the group of computer programming e-learners. Additionally, a significant regression equation was found in the group of respondents not participating in computer programming courses, $F(4, 206) = 6.394, p < 0.001$, with an $R^2 = 0.110$. Respondents' predicted flourishing was equal to $3.242 + 0.239$ (positive daily functioning) + 0.118 (positive future expectation) points. Flourishing increased 0.239 points for each positive daily functioning point and 0.118 points for each positive future expectation point. Positive daily functioning ($B = 0.239, p = 0.006$) and positive future expectation ($B = 0.118, p = 0.047$) contributed significantly to the model and were significant predictors of flourishing in the group of university students who studied social sciences remotely due to the COVID-19 pandemic.

Furthermore, to test H4, assuming that self-reported flourishing and positive automatic thoughts predict peer-to-peer confirmation of participants and non-participants of e-learning based computer programming courses, we firstly conducted multiple linear regression (forward method) analysis in the group of participants of e-learning based computer programming education. The results are displayed in Table 8.

Table 8. Multiple regression model, the dependent variables are student-to-student confirmation factors, and the predictors are self-reported flourishing and positive automatic thoughts; group of computer programming e-learners.

Dependent Variables	Predictors/ Models	Unstandardized Coefficients	Standardized Coefficients		<i>t</i>	Sig.	<i>R</i>	<i>R</i> ²	<i>F</i>	Sig.
		<i>B</i>	Std. Error	Beta						
Respondents participate in e-learning-based computer programming courses										
Student-to-Student confirmation	1 (Constant)	2.484	0.138		18.061	<0.001	0.398	0.159	45.283	<0.001
	Positive daily functioning	0.302	0.045	0.398	6.729	<0.001				
	2 (Constant)	2.114	0.228		9.270	<0.001	0.416	0.173	24.998	<0.001
	Positive daily functioning	0.209	0.064	0.276	3.289	0.001				
	Flourishing	0.173	0.085	0.171	2.031	0.043				
	3 (Constant)	2.027	0.227		8.917	<0.001	0.445	0.198	19.591	<0.001
	Positive daily functioning	0.306	0.072	0.405	4.244	<0.001				
	Flourishing	0.266	0.091	0.262	2.930	0.004				
	Positive future expectation	−0.169	0.062	−0.258	−2.726	0.007				

Table 8. Cont.

Dependent Variables	Predictors/ Models	Unstandardized Coefficients	Standardized Coefficients		<i>t</i>	Sig.	<i>R</i>	<i>R</i> ²	<i>F</i>	Sig.
		<i>B</i>	Std. Error	Beta						
Respondents participate in e-learning-based computer programming courses										
Individual attention	1 (Constant)	2.034	0.275		7.408	<0.001	0.339	0.115	31.114	<0.001
	Flourishing	0.407	0.073	0.339	5.578	<0.001				
	2 (Constant)	1.950	0.272		7.157	<0.001	0.378	0.143	19.978	<0.001
	Flourishing	0.274	0.086	0.228	3.180	0.002				
	Other evaluation of self	0.185	0.066	0.202	2.818	0.005				
	3 (Constant)	1.771	0.280		6.330	<0.001	0.405	0.164	15.529	<0.001
	Flourishing	0.414	0.103	0.344	4.013	<0.001				
	Other evaluation of self	0.252	0.071	0.274	3.562	<0.001				
	Positive future expectation	−0.171	0.071	−0.220	−2.414	0.017				
Acknowledgement	1 (Constant)	2.226	0.162		13.707	<0.001	0.367	0.135	37.316	<0.001
	Positive daily functioning	0.323	0.053	0.367	6.109	<0.001				
Assistance	1 (Constant)	2.570	0.169		15.171	<0.001	0.304	0.092	24.441	<0.001
	Positive daily functioning	0.273	0.055	0.304	4.944	<0.001				
	2 (Constant)	2.667	0.175		15.255	<0.001	0.329	0.108	14.485	<0.001
	Positive daily functioning	0.400	0.083	0.446	4.830	<0.001				
	Positive future expectation	−0.147	0.072	−0.189	−2.050	0.041				

In the computer programming e-learners, several significant regression equations were found concerning the factor of student-to-student confirmation. In model 1, the dependent variable was student-to-student confirmation, and the predictor was positive daily functioning, $F(1, 240) = 45.283$, $p < 0.001$, with $R^2 = 0.159$. Predicted student-to-student confirmation was equal to $2.484 + 0.302$ (positive daily functioning) points. Student-to-student confirmation increased 0.302 points for each positive daily functioning ($p < 0.001$) point. In model 2, the dependent variable was student-to-student confirmation, and the predictors were positive daily functioning and flourishing, $F(2, 239) = 24.998$, $p < 0.001$, with $R^2 = 0.173$. Predicted student-to-student confirmation was equal to $2.114 + 0.209$ (positive daily functioning) $+ 0.173$ (flourishing) points. Student-to-student confirmation increased $+0.209$ points for each positive daily functioning ($p = 0.001$) point and $+0.173$ points for each flourishing ($p = 0.043$) point. In model 3, the dependent variable was student-to-student confirmation, and the predictors were positive daily functioning, flourishing and positive future expectation, $F(3, 238) = 19.591$, $p < 0.001$, with $R^2 = 0.198$. Predicted student-to-student confirmation was equal to $2.027 + 0.306$ (positive daily functioning) $+ 0.266$ (flourishing) $- 0.169$ (positive future expectation) points. Student-to-student confirmation increased $+0.306$ points for each positive daily functioning ($p < 0.001$) point, $+0.266$ points for each flourishing ($p = 0.004$) point and decreased -0.169 for each positive future expectation ($p = 0.007$) point. Thus, positive daily functioning, flourishing and positive future expectation contributed significantly to the model and were significant predictors of student-to-student confirmation in computer programming e-learners.

Likewise, a significant regression equation was found regarding individual attention. In model 1, the dependent variable was individual attention, and the predictor was flourishing, $F(1, 240) = 31.114$, $p < 0.001$, with $R^2 = 0.115$. Predicted individual attention was equal to $2.034 + 0.407$ (flourishing) points. Individual attention increased $+0.407$ points for each flourishing ($p < 0.001$) point. In model 2, the dependent variable was individual attention, and the predictors were flourishing and other evaluation of self, $F(2, 239) = 19.978$, $p < 0.001$, with $R^2 = 0.143$. Predicted individual attention was equal to $1.950 + 0.274$ (flourishing) $+ 0.185$ (other evaluation of self) points. Individual attention increased $+0.274$ points for each flourishing ($p = 0.002$) point and $+0.185$ points for each other evaluation of self ($p = 0.005$) point. In model 3, the dependent variable was individual attention, and the predictors were flourishing, other evaluation of self and positive future expectation, $F(3, 238) = 15.529$, $p < 0.001$, with $R^2 = 0.164$. Predicted individual attention was equal to $1.771 + 0.414$ (flourishing) $+ 0.252$ (other evaluation of self) $- 0.171$ (positive

future expectation) points. Individual attention increased + 0.414 points for each flourishing ($p < 0.001$) point, + 0.252 points for each other evaluation of self ($p < 0.001$) point and decreased −0.171 points for each positive future expectation ($p = 0.017$) point. Thus, flourishing, other evaluation of self and positive future expectation contributed significantly to the model and were significant predictors of individual attention of computer programming e-learners.

Next, a significant regression equation was found concerning acknowledgement, $F(1, 240) = 37.316$, $p < 0.001$, with $R^2 = 0.135$. Predicted acknowledgement was equal to $2.226 + 0.323$ (positive daily functioning) points. Acknowledgement increased + 0.323 points for each positive daily functioning ($p < 0.001$) point. So, positive daily functioning was a significant predictor of acknowledgement of computer programming e-learners.

Finally, a significant regression equation was found concerning assistance. In model 1, the dependent variable was assistance, and the predictor was positive daily functioning $F(1, 240) = 24.441$, $p < 0.001$, with $R^2 = 0.092$. Predicted assistance was equal to $2.570 + 0.273$ (positive daily functioning) points. Assistance increased + 0.273 points for each positive daily functioning ($p < 0.001$) point. In model 2, the dependent variable was assistance, and the predictors were positive daily functioning and positive future expectation, $F(2, 239) = 14.485$, $p < 0.001$, with $R^2 = 0.108$. Predicted assistance was equal to $2.667 + 0.400$ (positive daily functioning) −0.147 (positive future expectation) points. Assistance increased + 0.400 points for each daily functioning ($p < 0.001$) point and decreased −0.147 points for each positive future expectation ($p = 0.041$) point. Thus, positive daily functioning and positive future expectation contributed significantly to the model and were significant predictors of assistance in the group of computer programming e-learners.

Next, a multiple linear regression model (enter method) was calculated to predict peer-to-peer confirmation based on positive automatic thoughts and flourishing in respondents not participating in e-learning-based computer programming courses. Surprisingly, in this group, no significant regression equations were found. It means, that in the group of social sciences e-learners, differently from computer programming e-learners, positive automatic thoughts and flourishing did not predict peer-to-peer confirmation. The results are displayed in Table 9.

Table 9. Multiple regression model, the dependent variables are student-to-student confirmation factors, and the predictors are self-reported flourishing and positive automatic thoughts; group of social sciences e-learners.

Dependent Variables	Predictors/ Models	Unstandardized Coefficients	Standardized Coefficients		<i>t</i>	Sig.	<i>R</i>	<i>R</i> ²	<i>F</i>	Sig.
		<i>B</i>	Std. Error	Beta						
Respondents do not participate in e-learning-based computer programming courses										
Student-to-Student confirmation	(Constant)	2.803	0.362		7.738	<0.001	0.167	0.028	1.181	0.320
	Positive daily functioning	−0.019	0.112	−0.023	−0.172	0.863				
	Positive self-evaluation	−0.032	0.109	−0.038	−0.293	0.770				
	Other evaluation of self	0.135	0.100	0.149	1.354	0.177				
	Positive future expectation	0.003	0.076	0.004	0.037	0.971				
	Flourishing	0.135	0.089	0.111	1.518	0.130				
Individual attention	(Constant)	3.024	0.396		7.638	<0.001	0.142	0.020	0.846	0.519
	Positive daily functioning	−0.047	0.122	−0.052	−0.385	0.701				
	Positive self-evaluation	0.010	0.119	0.011	0.084	0.933				
	Other evaluation of self	0.110	0.109	0.111	1.011	0.313				
	Positive future expectation	0.010	0.083	0.012	0.121	0.904				
	Flourishing	0.129	0.097	0.097	1.324	0.187				

Table 9. Cont.

Dependent Variables	Predictors/ Models	Unstandardized Coefficients	Standardized Coefficients		<i>t</i>	Sig.	<i>R</i>	<i>R</i> ²	<i>F</i>	Sig.
		<i>B</i>	Std. Error	Beta						
Respondents do not participate in e-learning-based computer programming courses										
Acknowledgement	(Constant)	2.487	0.406		6.119	<0.001	0.170	0.029	1.214	0.304
	Positive daily functioning	−0.057	0.126	−0.061	−0.458	0.647				
	Positive self-evaluation	−0.065	0.122	−0.068	−0.528	0.598				
	Other evaluation of self	0.176	0.112	0.173	1.581	0.115				
	Positive future expectation	0.029	0.085	0.034	0.342	0.732				
	Flourishing	0.149	0.100	0.109	1.494	0.137				
Assistance	(Constant)	2.910	0.408		7.128	<0.001	0.162	0.026	1.106	0.359
	Positive daily functioning	0.084	0.126	0.090	0.668	0.505				
	Positive self-evaluation	−0.053	0.123	−0.056	−0.432	0.666				
	Other evaluation of self	0.114	0.112	0.111	1.013	0.312				
	Positive future expectation	−0.049	0.085	−0.056	−0.569	0.570				
	Flourishing	0.124	0.100	0.091	1.243	0.215				

Furthermore, to test H5, which assumed that there exist associations between self-reported flourishing, positive automatic thoughts, and student-to-student confirmation, but they differ between participants and non-participants of e-learning based computer programming courses, we have conducted an SEM analysis. Standardized results of the model are presented in Figure 1. Model fit was evaluated based on the CFI (Comparative Fit Index), the Normed Fit Index (NFI), the Tucker–Lewis coefficient (TLI), and RMSEA (Root Mean Square Error of Approximation). As mentioned above, the values higher than 0.90 for CFI, NFI, TLI, and values lower than 0.08 for RMSEA indicate a good fit. Findings revealed that the fit of the model was good, $\chi^2 = 81.320$, $df = 36$, $p < 0.001$; NFI = 0.963; TLI = 0.967; CFI = 0.979; RMSEA = 0.075 [0.053–0.096]; SRMR = 0.033.

Figure 1. Standardized results of the model on associations between self-reported flourishing, positive automatic thoughts, and student-to-student confirmation in both groups of participants and non-participants of computer programming e-learning based courses. ACK: acknowledgement; IA: individual attention; AS: assistance; PDF: positive daily functioning; OES: other evaluation of self; PSE: positive self-evaluation; PFE: positive future expectation; ns: non-significant, parentheses inside the constructs indicate R^2 values.

Scalar estimates of the model on associations between self-reported flourishing, positive automatic thoughts, and student-to-student confirmation in both groups of participants and non-participants of computer programming e-learning based courses are presented in Table 10.

Table 10. Scalar estimates of the model on associations between self-reported flourishing, positive automatic thoughts, and student-to-student confirmation in groups of participants and non-participants of computer programming e-learning based courses.

Regression			B	S.E.	Z	p	LL	UL	β	R ²	Group *
Student-to-student confirmation	→	Positive automatic thoughts	0.623	0.114	5.485	<0.001	0.400	0.845	0.417	0.174	1
Positive automatic thoughts	→	Flourishing	0.557	0.048	11.697	<0.001	0.464	0.650	0.706	0.574	1
Student-to-student confirmation	→	Flourishing	0.128	0.089	1.434	0.151	−0.047	0.303	0.109		1
Student-to-student confirmation	→	Positive automatic thoughts	0.139	0.116	1.192	0.233	−0.089	0.367	0.110	0.093	2
Positive automatic thoughts	→	Flourishing	0.212	0.059	3.609	<0.001	0.097	0.327	0.281	0.012	2
Student-to-student confirmation	→	Flourishing	0.089	0.068	1.305	0.192	−0.045	0.222	0.093		2
Measurement Model											
Positive automatic thoughts	→	Positive daily functioning	1.000	0.000			1.000	1.000	0.945	0.894	1
Positive automatic thoughts	→	Other evaluation of self	0.831	0.044	18.907	<0.001	0.745	0.917	0.803	0.646	1
Positive automatic thoughts	→	Positive self-evaluation	0.913	0.045	20.410	<0.001	0.825	1.000	0.867	0.751	1
Positive automatic thoughts	→	Positive future expectation	0.989	0.055	18.033	<0.001	0.881	1.096	0.810	0.657	1
Student-to-student confirmation	→	Acknowledgement	1.000	0.000			1.000	1.000	0.718	0.515	1
Student-to-student confirmation	→	Individual attention	1.215	0.128	9.472	<0.001	0.963	1.466	0.857	0.735	1
Student-to-student confirmation	→	Assistance	0.976	0.112	8.704	<0.001	0.756	1.195	0.688	0.473	1
Positive automatic thoughts	→	Positive daily functioning	1.000	0.000			1.000	1.000	0.910	0.828	2
Positive automatic thoughts	→	Other evaluation of self	0.823	0.042	19.398	<0.001	0.740	0.906	0.813	0.660	2
Positive automatic thoughts	→	Positive self-evaluation	0.978	0.045	21.676	<0.001	0.889	1.066	0.895	0.800	2
Positive automatic thoughts	→	Positive future expectation	0.891	0.074	12.081	<0.001	0.746	1.035	0.742	0.551	2
Student-to-student confirmation	→	Acknowledgement	1.000	0.000			1.000	1.000	0.769	0.591	2
Student-to-student confirmation	→	Individual attention	1.184	0.098	12.066	<0.001	0.992	1.377	0.939	0.881	2
Student-to-student confirmation	→	Assistance	1.076	0.089	12.070	<0.001	0.901	1.250	0.824	0.680	2

* Group 1: participants of e-learning based computer programming courses; Group 2: non-participants of e-learning based computer programming courses.

The SEM analysis showed that student-to-student confirmation does not predict flourishing in both sample groups. Student-to-student confirmation statistically significantly

predicts positive automatic thoughts only in the computer programming e-learners group, and student-to-student confirmation explains 17.4% of the variance of positive automatic thoughts. Positive automatic thoughts statistically significantly predict flourishing in both sample groups. Student-to-student confirmation and positive automatic thoughts explain 57.4% of the variance of flourishing in the computer programming e-learners group and 9.3% in the social sciences e-learners group.

4. Discussion

This study was the first to explore associations between positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation in e-learning-based education, including computer programming learning, during the COVID-19 pandemic. The relationship between peer-to-peer confirmation and mental health has been extensively studied [30,34,35,79]. Most of the previous studies targeted educational variables, such as learning motivation [34,35] and mental health indicators, such as depression and anxiety [1], with a narrow focus on psychological wellbeing [79]. This study primarily targeted the positive psychology construct of flourishing and positive automatic thoughts in relation to peer-to-peer confirmation in e-learning. The examination of positive automatic thoughts was based on a model developed by Ingram and Wisnicki [17]; the examination of flourishing was based on a model developed by Diener et al. [42], and the examination of peer-to-peer confirmation was based on a model developed by LaBelle and Johnson [35]. The context of the COVID-19 quarantine, which brought the rapid implementation of e-learning [80], helped us compare positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation in e-learning-based computer programming education and e-learning education in social sciences. It also revealed some specifics of associations between the study variables in different samples.

4.1. Computer Programming E-Learners Differ from Other E-Learners in Flourishing and Positive Daily Functioning

In this study, we assumed (H1) that computer programming e-learners do not differ in their positive automatic thoughts and self-reported flourishing from other e-learners. This assumption was based on previous research indicating that computer programming learners do not demonstrate higher scores on personality trait neuroticism [78], which is related to negative thoughts [102] and diminished flourishing [103,104]. Thus, we have conducted the independent samples T-test and compared the scores of positive automatic thoughts and self-reported flourishing in both groups. The results partially confirmed this hypothesis, as no significant differences between the groups were found in positive automatic thoughts, positive self-evaluation, other evaluation of self, and positive future expectations. However, T-test analysis has revealed some significant differences between the samples. Surprisingly, university students who studied social sciences demonstrated higher scores of positive daily functioning and flourishing than participants of e-learning based computer programming education. These results might be partially explained by previous research suggesting that flourishing is related to social wellbeing [42,45,47,49,105]. However, it is unclear why computer programming e-learners differed from e-learners in social sciences in flourishing and positive daily functioning but did not differ in positive automatic thoughts, positive self-evaluation, other evaluation of self, and positive future expectation. Due to the relatively small sample size, these findings should be taken with caution and needs further investigation, especially establishing links between positive psychology constructs, personality traits, and objective indicators.

4.2. Computer Programming E-Learners Differ in Their Peer-to-Peer Confirmation from Other E-Learners

Furthermore, we presumed (H2) that computer programming e-learners differ in their peer-to-peer confirmation from other e-learners. This assumption was based on previous research which revealed that computer programming e-learners demonstrated lower scores of extraversion [78], which is linked to social connectedness [106]. Hence,

we conducted the independent samples' T-test, which revealed statistically significant differences between the groups. As expected, non-participants of computer programming e-learning courses demonstrated higher scores of a peer-to-peer confirmation than participants of computer programming e-learning courses. University students in social sciences demonstrated higher scores of individual attention than participants of e-learning based computer programming education. In addition, non-participants demonstrated higher scores of acknowledgement than computer programming e-learners. Moreover, non-participants of e-learning based computer programming education demonstrated higher scores of assistance in comparison to participants. These studies align with prior research on personality traits and social connectedness [106,107]. However, as this study did not directly link personality traits to peer-to-peer confirmation, these results must be regarded with caution and need further examination.

4.3. Positive Automatic Thoughts Partially Predict the Flourishing of Computer Programming and Other E-Learners

Next, we assumed (H3) that positive automatic thoughts predict self-reported flourishing in both groups of participants and non-participants of e-learning based computer programming courses. This assumption was based on positive psychology and cognitive behaviour therapy research, evidencing that thoughts affect psychological well-being [106,108,109]. Hence, we conducted multiple linear regression analyses, which showed that in the group of students of computer-based e-learning education and in the group of university students who studied social sciences remotely due to the COVID-19 pandemic, positive daily functioning and positive future expectation predicted self-reported flourishing. These findings support extensive studies suggesting links between positive thoughts and psychological wellbeing [106,108–111]. However, it is unclear why flourishing was predicted just by positive daily functioning and positive future expectations. This study indicated no significant effects of positive self-evaluation and other evaluations of self, which are also indicators of positive automatic thoughts [17]. Therefore, these results need further investigation.

4.4. Positive Automatic Thoughts and Flourishing Predict Peer-to-Peer Confirmation in Group of Computer Programming E-Learners

Furthermore, we presumed (H4) that self-reported flourishing and positive automatic thoughts predict peer-to-peer confirmation of participants and non-participants of e-learning based computer programming courses. This premise was based on previous research indicating that peer-to-peer confirmation and interactions are linked to the positive effect for the course, the instructor, and the content [33,35,112], greater mental well-being among college students [110] and in other contexts [113]. Therefore, we conducted multiple linear regression analysis, which showed that in the group of computer programming e-learners, peer-to-peer confirmation was predicted by positive daily functioning (model 1), positive daily functioning and flourishing (model 2), positive daily functioning, flourishing, and positive future expectations (model 3). Likewise, individual attention was predicted by flourishing (model 1), flourishing and other evaluation of self (model 2), flourishing, other evaluation of self and positive future expectations (model 3). Next, acknowledgement was predicted by positive daily functioning. Finally, assistance was predicted by positive daily functioning (model 1), positive daily functioning and positive future expectations (model 2). These results support previous findings suggesting links between interpersonal interactions, positive thinking and wellbeing [33,35,42,49,79,105,110,112,113]. Surprisingly, no significant regression equations were found in the group of respondents not participating in e-learning-based computer programming courses. It means that in the group of social sciences e-learners, differently from computer programming e-learners, positive automatic thoughts and flourishing did not predict peer-to-peer confirmation. These findings partially contradict some previously mentioned studies, which evidenced links between peer support, thinking patterns, and psychological wellbeing, and need further examination.

4.5. Associations between the Study Variables Partially Differ in the Compared Groups

Based on a literature review and previous analyses, we assumed (H5) that associations between self-reported flourishing, positive automatic thoughts, and peer-to-peer confirmation exist, but they differ between participants and non-participants of e-learning based computer programming courses. Thus, we tested several models of associations between these study variables. The findings partially confirmed the hypothesis and identified several possible paths and models of associations between self-reported flourishing, positive automatic thoughts, and peer-to-peer confirmation in groups of participants and non-participants of e-learning-based computer programming courses. The SEM analysis revealed that peer-to-peer confirmation did not predict flourishing in both sample groups. Peer-to-peer confirmation statistically significantly predicted positive automatic thoughts only in the computer programming e-learners group, and in this group, peer-to-peer confirmation explained 17.4% of the variance of positive automatic thoughts. Positive automatic thoughts statistically significantly predicted flourishing in both sample groups. Peer-to-peer confirmation and positive automatic thoughts explained 57.4% of the variance of flourishing in the computer programming e-learners group and 9.3% of the flourishing variance in the social sciences e-learners group. These results signify the importance of peer-to-peer confirmation and positive thoughts for computer programming e-learners' psychological wellbeing.

To summarize, this study demonstrated that associations between self-reported flourishing, positive automatic thoughts, and peer-to-peer confirmation differ between participants and non-participants of e-learning-based computer programming courses. The effect of peer-to-peer confirmation and positive thoughts was almost six times larger for computer programming e-learners.

The findings on associations between self-reported flourishing, positive automatic thoughts, and peer-to-peer confirmation are consistent with many previous studies suggesting the links between positive automatic thoughts, psychological wellbeing, and peer connectedness [33,35,79,105,110,112–115]. However, the mechanism underlying the links' specifics in different samples is still unclear and needs further investigation. In the future, it would be essential to identify the underlying mechanisms in associations between peer-to-peer confirmation factors and the positive states of computer programming e-learners.

4.6. Theoretical Implications

From a theoretical perspective, this study was the first of its kind to explore the associations between positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation in e-learning-based education, including computer programming learning, during the COVID-19 pandemic. From a perspective of sustainability, well-being is a key sustainable development goal [116], and this study adds to the psychology of sustainability and sustainable development, which highlight sustainable development of every person, facilitating the flourishing of his/her intrapersonal talents and also emphasizes well-being in different kinds of environments [116].

Even though the relationship between peer-to-peer confirmation and mental health has been broadly researched, most of the previous studies targeted educational variables and mental health indicators, with a limited focus on psychological wellbeing [1,79]. This study primarily targeted the positive psychology construct of flourishing and positive automatic thoughts. The findings were consistent with previous studies suggesting associations between the positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation [33,35,79,105,110,112–115], and it also revealed the complexity of the relations between positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation in groups of computer programming and social sciences e-learners. It is unclear why the effect of peer-to-peer confirmation and positive thoughts was almost six times larger for computer programming e-learners, and why positive automatic thoughts and flourishing predicted peer-to-peer confirmation just in group of computer programming e-learners. It is also unclear why flourishing was predicted just by positive

daily functioning and positive future expectations, and not by positive self-evaluation and other evaluation of self, which are also indicators of positive automatic thoughts [17]. In the future, it would be valuable to identify the computer programming and other e-learners' underlying mechanisms in associations between peer-to-peer confirmation factors and positive states, which have recently received the increased attention of researchers [117], as a constructive change of beliefs (attitudes, knowledge, information structures) and, consequently, behaviours are central to reach sustainable development goals and facilitate personal and environmental flourishing [116].

4.7. Practical Implications

Research indicates that due to the COVID-19 pandemic, online learning has been adopted in all stages of education, and this sudden change could affect students' learning effectiveness [8,80,118]. Computer programming education also faced challenges that affected the world during the quarantine [1]. Some students developed emotional difficulties related to stressful life circumstances [9], which affected satisfaction with e-learning [10], or led to diminished e-learning motivation or even absence of it [11]. However, the cognitive model of emotional difficulties suggests that psychological wellbeing mainly depend not on life circumstances themselves [12], but on cognitive processes, which may manifest in positive or negative automatic thoughts [13–16]. Positive automatic thoughts promote psychological well-being [17], which is linked to many positive educational outcomes [23,24]. This study explored the role of cognitive specificity of beliefs in self-reported psychological flourishing and peer-to-peer confirmation. The results revealed that positive automatic thoughts significantly contribute to the flourishing of e-learners and promote peer-to-peer confirmation of computer programming e-learners. The findings on associations between positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation in e-learning based education imply that education policymakers, researchers, and educators, to promote learners' flourishing, which is linked to academic achievements [23,24], should target e-learners' beliefs and peer-to-peer confirmation. Focus on e-learners' beliefs and flourishing would also assist in promoting the sustainable happiness of a person and society as the whole, as sustainability is defined not only in terms of the ecological and socio-economic environment but also in terms of improving the quality of life of every human being [116] and introduces a framework focused on a positive approach based on keywords such as promotion, enrichment, growth, flexible change [119].

4.8. Limitations and Future Directions

Several limitations to this study can be revealed. First, this study lacks a solid unifying theoretical basis because it applied constructs based on different theoretical models. Second, bias may have occurred due to using self-reported measures only and the omission of objective indicators. Third, considering that the data were collected online, these findings should be regarded with caution. Fourth, the research samples were not representative, suggesting the necessity to analyze representative samples of e-learners; thus, generalizations should be made with concern. Next, although the sample size satisfied the minimal requirements for the applied statistical models, and the data fit was acceptable, the results should be regarded cautiously due to the relatively small sample size. Furthermore, this study was conducted in Lithuania, and the results may reflect the cultural specifics of this area, suggesting the necessity to analyze the impact of cultural factors, considering the more specific aspects of each culture. Finally, the findings suggest a necessity for longitudinal or experimental research design because, based on the data obtained, it is possible only to identify significant relationships among the examined variables. Thus, the conclusions should be cautioned, especially regarding causality, because reverse causality is also likely to occur.

5. Conclusions

This study targeted positive automatic thoughts, self-reported psychological flourishing, and peer-to-peer confirmation of computer programming e-learners. The findings revealed that computer programming e-learners differed from other e-learners in flourishing, positive daily functioning, and peer-to-peer confirmation. In both samples, positive daily functioning and positive future expectations predicted self-reported flourishing. Positive automatic thoughts and flourishing predicted peer-to-peer confirmation just in the group of computer programming e-learners. Peer-to-peer confirmation and positive automatic thoughts explained 57.4% of the variance of flourishing in the computer programming e-learners group and 9.3% of the flourishing variance in the social sciences e-learners group. These results signify the importance of peer-to-peer confirmation and positive thoughts for computer programming e-learners' psychological wellbeing. Nevertheless, the results of this particular study should be regarded with caution due to the relatively small sample size and other limitations.

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