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Factors contributing to dropping out of adults' programming e-learning

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A R T I C L E I N F O

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A B S T R A C T

Previous studies reported that acquiring computer programming skills is challenging and might result in high dropout rates. A quasi-experimental design was used to examine the role of different factors in dropping out of an e-based computer programming course. This study applied a knowledge in programming assessment test (20 multiple-choice questions covering the following topics: variables, loops, conditionals, functions, and general knowledge of Python), The Learning Motivating Factors Questionnaire, The Big Five-2, and The Basic Psychological Need Satisfaction & Frustration Scale. Ninety-four participants (38 males and 56 females) completed the course, while 305 participants started it. The mean age of e-learners was 29.96 years (SD 8.27), age range = 18 to 54. The results showed that e-learners who completed the course had higher initial knowledge assessment scores than those who dropped out after the first assessment. Reward and recognition as a motivator were significantly higher in males who completed the course than those who dropped out after the second knowledge assessment. Extraversion was significantly lower in females who completed the course than those who dropped after the first or second knowledge assessment test. Relatedness frustration was significantly higher in those who dropped out after the first knowledge assessment. Due to significant limitations of the sample size, cultural context, measures applied, and research design, the findings would preferably be regarded with caution.

1. Introduction

In the era of fast technological advancement, computer programming skills are vital for professionals in many job sectors [1]. The emergence of Web 2.0 and Web 3.0 tools has facilitated new learning environments and introduced innovative programming learning methods, promoting a shift towards self-regulated e-learning [2]. Despite this, learning computer programming is still highly challenging for many learners [3], and the dropout rates in computer programming courses are almost the highest among other disciplines

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[4]. Moreover, research indicates that online courses have significantly higher dropout rates than conventional ones [5,6], as e-learners face many challenges, such as motivation, time management, and self-monitoring [7].

Recent studies revealed that learners could structure their e-learning [2]. Despite that, students' efforts to self-regulate their e-learning are average; they tend to discontinue their learning when they lose focus or when the material is too complicated [2]. Learners' satisfaction with online studies is relatively low, as the study process is stressful and complex [8], students struggle with time management and retaining motivation, they face problems of inequality and digital division [7].

Previous research also revealed that peer relationships are a protective factor that accounts for students' achievements and depressive symptoms [9]. Learners with few friends at university and low self-regulated learning self-efficacy are considered to drop out more often than those with good peer relationships [10]. However, the learning analytics model might prevent students from dropping out of higher education institutions [11].

Previous studies indicated that dropping out of computer programming learning is related to learning motivation [12,13], academic achievements [14], interest in the subject [15], intra-individual changes in intrinsic value (similar to interest) [16] and other learner characteristics [17], course design, and learning context [18], or lack of collaborative work [19,20]. However, the whole set of variables related to dropping out of computer programming e-learning is still under-researched.

This study aims to provide answers to the following research questions.

1. How do initial grades affect the dropping out of computer programming e-learning courses?
2. How does learning motivation contribute to the dropouts of computer programming e-learning courses?
3. Do personality traits contribute to the dropouts of computer programming e-learning courses?
4. What role does the satisfaction/frustration of basic psychological needs play in completing the courses of computer programming e-learning or dropping out?
5. What role does gender play in completing the course of computer programming e-learning or dropping out of it?

1.1. The role of achievements

There are many conceptual frameworks for explaining the dropout phenomenon. While student involvement theory [21], the student integration model [22], the general model for assessing change [23], and the model of dropping out of residential and commuter colleges [24] are the primary models clarifying the factors related to dropping out in higher education, the frustration-self-esteem, and participation-identification models, proposed by Finn [25], enlightens the path to dropout. According to Finn, a learning failure or low achievement diminish a learner's self-esteem, subsequently increasing the risk of dropping out. Vice versa, each learning achievement, followed by higher self-esteem, contributes to learning involvement and leads to completion. Learners' self-esteem is widely studied at the secondary-school level [26–28]. Could this theory be applied in post-secondary education of computer programming e-learning? As the most considerable number of dropouts occurs in the initial stages of learning [15,29], can the initial achievements contribute to successful completion? Research indicates that students' self-efficacy and self-esteem are significant predictors of dropouts [16,30]. Consequently, achievement frustration might diminish self-esteem and self-efficacy. Based on the conceptual model of frustration-self-esteem, in this study, the first hypothesis (H1) was defined: Low initial knowledge assessment scores in computer programming e-learning play a significant role in dropout.

1.2. Learning motivating factors

Previous studies revealed that a history of grade retention, learning difficulties, and low academic achievements might significantly impact students' dropout rates [33]. Among the many antecedents of dropout, researchers indicate three main factors: student, course, and environmental [34].

Many studies reported the reasons for not completing massive open online courses (MOOC): informational overload, lack of motivation [35], limited feedback [36], disrupted communication [37–39], course design and content related problems [40], social and environmental factors [41], learner's academic skills and abilities, prior experience, course design, feedback, social presence, and social support [18]. Many of these findings suggest explicit links between dropping out and learning motivation.

Some studies identified several learning motivation factors: individual attitude and expectation, reward and recognition, challenging goals, social pressure, and competition [42,43], or the importance of these factors in computer programming e-learning [44]. Shah, J., & Khanna, M [45]. found that perceived usefulness, hedonic motivation, information quality, and system quality positively impact satisfaction with MOOCs. Moreover, perceived usefulness, hedonic motivation, and satisfaction significantly influence the continued MOOCs use intention. Kehm et al. reviewed 44 studies and concluded that intrinsic learning motivation significantly reduces dropout, while the effect of extrinsic motivation is blurred [46].

Overall, research indicates that learning motivation is a crucial factor in determining learning outcomes ([47–49] as motivated learners put in more effort, are more attentive and more persistent in the face of difficulties [32], while not motivated learners are at risk to drop out. Based on these findings, hypothesis (H2) was proposed: Learning motivation of computer programming e-learners plays a significant role in dropout.

1.3. Personality traits

Furthermore, recent studies reported associations between dropping out and personal characteristics [35,50,51]. Kehm et al. concluded that personal characteristics could affect retention [46].

Some researchers suggest that the personalization of courses based on learner characteristics can efficiently prevent dropouts. Kolb's Learning Style Theory (KLSI), based on Experiential Learning Theory (ELT) and built upon the idea that learning preferences can be described by using two continuums: active-reflective and abstract-concrete, identifies four types of learners: active-abstract (Converging), active-concrete (Accommodating), reflective-abstract (Assimilating), and reflective-concrete (Diverging). Some studies have reported the possible impact of these characteristics on course completion [52–55]. However, some research revealed that these characteristics are unstable, and learners can adapt their personal styles to succeed in a web-based learning environment [56].

Personality traits are relatively stable personal characteristics related to the dropout phenomenon. The five-factor, or Big Five model, validated in clinical, educational, and other contexts [57], lists the five broadest personality traits: extraversion, neuroticism, openness to new experiences, conscientiousness, and agreeableness [58]. Research suggests that each personality trait can differently impact the intention to persevere in online learning and not drop out. Al-Qirim et al. [59] found that most users of an online learning platform scored high on agreeableness, extraversion, and conscientiousness, whereas neuroticism scored the lowest. Other studies confirmed that agreeableness, extraversion, and conscientiousness play a significant positive role in the intention to continue learning [60]. However, the impact of personality traits on computer programming e-learning was under-researched. Based on the previous studies, hypothesis (H3) was defined: Personality traits of computer programming e-learners play a significant role in dropout.

1.4. Basic psychological needs

Some studies have indicated the indirect importance of learners' basic psychological needs satisfaction or frustration for dropouts [61]. The construct of basic psychological needs (competence, relatedness, autonomy) emerged within the self-determination theory ([62] and has recently been widely applied in educational research. Many studies suggest that the satisfaction of learners' basic psychological needs is related to psychological well-being [61], learning motivation [63], academic success [19], and academic engagement [64].

However, some research would raise more questions regarding the findings supporting the importance of basic needs satisfaction or frustration in dropping out. A study by Terrell revealed that students with a preference for systematic planning and an intellectual understanding of a situation are more likely to succeed than students preferring concrete experience and interaction with other students [56]. Is satisfaction/frustration with the need for competence more critical than the need for relatedness? How does satisfaction/frustration of basic psychological needs contribute to learning continuation or dropping out? Based on partly contradictory findings, the fourth hypothesis (H4) was proposed: Satisfaction/frustration of basic psychological needs of computer programming e-learners play a significant role in dropout.

1.5. The role of gender

Previous studies have demonstrated that the dropout rate of females is much lower than that of males, and males face a higher risk of dropping out [65]. Furthermore, male dropouts were related to negative learners' attitudes [33]. Next, the factors contributing to dropouts in groups of females and males were partly different [66]. However, previous studies have not compared personality traits, basic psychological needs satisfaction/frustration, or learning motivating factors in groups of females and males who dropped out of the courses of computer programming e-learning or completed it. Based on the previous studies, hypothesis (H5) proposes: Gender plays a significant role in completing or dropping out of the course.

The present study addresses the role of starting grades (achievements), personality traits, learning motivation, and satisfaction/frustration of basic psychological needs in dropping out of computer programming e-learning courses. As some previous studies indicated gender differences in dropouts and related psychological variables, it was also assumed that gender plays a significant role in the dropout phenomenon. The dependent variable in this research was a dropout. The independent variables were grades of the initial evaluation of knowledge and skills in Python programming, personality traits, learning motivation, and basic psychological needs satisfaction/frustration of computer programming e-learners. It was presumed that withdrawers differ from non-withdrawers of computer programming e-learning courses in (H.1.1.) initial scores (first evaluation of knowledge in a programming language), learning motivation (H.2.1.) personality traits (H.3.1.), and satisfaction/frustration of basic psychological needs (H.4.1.). Next, the links between dropping out and initial scores (H.1.2.), learning motivation (H.2.2.), personality traits (H.3.2.), and satisfaction/frustration of basic psychological needs (H.4.2.) were assumed. Finally, we hypothesized that gender plays a significant role in completing the course or dropping out of it (H.5), and we presumed differences in initial knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females and males who dropped out of the course of computer programming e-learning (H.5.1). In addition, we assumed differences in initial knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females and males who completed the course of computer programming e-learning (H.5.2).

2. Materials and methods

2.1. Data collection and study sample

A quasi-experimental design was used to examine the role of different factors in dropping out of a short-term e-based Python programming course. The participants were taking the course at various times between January 5, 2021 and April 15, 2022. The variables were tested with a group of students with no control group. The quasi-experiment was chosen because the study was carried out in the development stage of an e-learning platform, where randomly assigning participants to groups was impossible. The research was carried out on naturally occurring groups of those who finished and those who dropped out after the first or the second knowledge assessment test. The quantitative research approach was chosen to evaluate the experiment. This paper presents the findings on the role of the first knowledge assessment test scores, personality traits, learning motivating factors, and basic psychological needs satisfaction/frustration in dropping out from e-based computer programming courses.

The data were collected from January 5, 2021 until April 15, 2022. The study sample consisted of computer programming students who studied e-learning-based computer programming courses organized by Turing College.

Social media (Facebook, Linkedin, and Instagram) was used to invite the respondents to voluntarily participate in the study. The respondents were informed about the research and provided informed consent. They were assured their information would be kept confidential and reminded that they were free to quit participation in the study at any time. Participants received no financial compensation for participation in the study, except they could improve their knowledge and skills in Python programming and stress management without paying for it. The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Institutional Review Board of the Institute of Management and Psychology, based on the approval of the Biomedical Research Ethics Committee at KU, No. STIMC-BMTEK-P03.

After registration for the computer programming e-learning course, participants were directed to the specific website psytest.online to fill in psychological questionnaires. The approximate duration of completing the questionnaires was 45–60 min. Afterward, the participants got a link directing to the first test, which evaluates the knowledge in Python programming. The test consisted of 20 multiple-choice questions covering the following topics: variables, loops, conditionals, functions, and general knowledge of Python. The questions were created with expected difficulty levels: easy, medium, and hard count. After completing the first knowledge assessment test, the participant received: a) a link to the content material, b) Discord connection instructions, and c) a note that the course must be completed within seven days. The programming course consisted of material prepared by professionals to improve general knowledge in Python and covered Python syntax, variables, loops, conditional statements, and basic of functions. After completing all the tasks, the participants were given the same test of knowledge assessment (20 questions) for a second time, after which the subjects were given feedback on the performance of the tasks. The feedback was provided by a programming expert (mentor) or a fellow student, depending on the study group in which a particular subject was involved. After providing feedback, participants were given the same knowledge assessment test for the third time (20 questions).

Ninety-six participants completed the computer programming training, while 313 participants started it. Successful completion of the training was considered if participants completed all three stages, i.e., have fully taken the course and taken the knowledge test three times with passing grades.

Three hundred thirteen students participated in this quasi-experiment. After data cleaning (Table 1), the sample consisted of N 305 participants. Because the number of cases with missing values was small, listwise deletion of cases with missing values was used. Therefore, all analyses were conducted using a sample of 305 individuals. Their mean age was 29.96 years (SD 8.27), age range = of 18–54. Among them, 39,9 % of participants had a bachelor's degree, 23,3 % had a master's degree, 2,6 % had a doctoral degree, and the rest were still pursuing a bachelor's degree. 100 % of the participants had Lithuanian citizenship.

This paper presents just some data from the quasi-experiment; therefore, the description of the irrelevant procedure parts for this paper was omitted.

2.2. Instruments

Learning motivation. The Learning Motivating Factors Questionnaire (LMFQ; [43,67], which consists of 20 items and covers several motivational variables that positively affect learning, was applied to assess learning motivation. The participants rated each item on a six-point Likert scale. The previous studies validated the questionnaire [43]. In this study, the CFA analysis confirmed the reliability and validity of the instrument [68,69], and the six-factor structure, CFI = 0.981; TLI = 0.976; RMSEA = 0.042 [0.036–0.049]; SRMR = 0.057; Cronbach α = 0.881.

Table 1
Number of participants in the quasi-experiment (computer programming e-learning).

Measure	Full sample		Males		Females	
	n	%	n	%	n	%
1st knowledge assessment	305	100	128	100	177	100
2nd knowledge assessment	118	37.7	52	40.6	66	37.3
3rd (completed the course)	94	30.0	38	29.7	56	31.6

Personality traits. The Big Five-2 (BFI-2; [58], which consists of 20 items and assesses extraversion, neuroticism, agreeableness, conscientiousness, and openness to experience, was applied to evaluate personality traits. The respondents rated each item on a five-point Likert scale. The BFI-2 was validated in prior studies [58]. In this study, the CFA analysis confirmed the five-factor structure, CFI = 0.831; TLI = 0.824; RMSEA = 0.076 [0,074–0.077]; SRMR = 0.089; *Extraversion* Cronbach α = 0.821; *Agreeableness* Cronbach α = 0.778; *Conscientiousness* Cronbach α = 0.840; *Neuroticism* Cronbach α = 0.902; *Open-Mindedness* Cronbach α = 0.682.

Satisfaction or frustration of psychological needs. The Basic Psychological Need Satisfaction & Frustration Scale (BPNSFS; [70], which consists of 24 items and assesses satisfaction/frustration of needs for autonomy, competence, and relatedness, was applied. Participants rated each statement on a five-point Likert scale. The BPNSFS was validated in previous studies [70]. In this study, the CFA analysis confirmed the six-factor structure, CFI = 0.944; TLI = 0.934; RMSEA = 0.057 [0.042–0.069]; SRMR = 0.043; Cronbach α = 0.936.

2.3. Data analysis

To analyze the data, SPSS, version 26, and JASP, version 16.1 were usedFirstly, CFA (confirmatory factor analysis) was applied and Cronbach's α was calculated to explore the validity and reliability of the instruments. Then, the normality of the data distribution was checked. Although the Shapiro-Wilk test showed a departure from normality, but distribution was considered normal as skewness and kurtosis did not exceed the range from −1 to 1 [71].

The descriptive statistics and the Pearson correlations between the study variables were calculated. Then the independent samples' T-test and a one-way ANOVA were applied to evaluate the differences between withdrawers and non-withdrawers in grades (knowledge assessment), personality traits, learning motivation, and basic psychological needs satisfaction/frustration. A logistic regression model was performed to see whether initial knowledge assessment test scores, personality traits, learning motivation, and basic psychological needs satisfaction/frustration predict the odds of an individual's completing the course or dropping out. In this study, p-values less than 0.05 were considered as statistically significant [72].

3. Results

Correlation analysis of the study variables (Table 2) revealed weak, but significant positive links between the initial grades and challenging goals and autonomy satisfaction ($p < 0.05$) and negative links between grades and autonomy frustration and relatedness frustration ($p < 0.05$). Interestingly, learning motivating factors clear direction and challenging goals were significantly positively related to extraversion, conscientiousness, open-mindedness, and agreeableness ($p < 0.001$), and negatively related to neuroticism ($p < 0.001$). Competence frustration and autonomy frustration were significantly negatively related to individual attitude and expectation, challenging goals, and clear direction as motivators ($p < 0.001$). Surprisingly, punishment was not significantly linked to any of the personality traits nor psychological needs' satisfaction/frustration, and social pressure and competition was significantly positively linked to extraversion ($p < 0.001$) and autonomy, relatedness, and competence satisfaction ($p < 0.05$). Thus, the results revealed some significant links between initial grades, some of the learning motivating factors, personality traits, and basic psychological needs' satisfaction/frustration.

The results of the Independent samples' T-test, comparing the study variables (first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration) in groups of females who dropped out and completed the course of computer programming e-learning are displayed in Table 3. As observed, females who dropped out of computer programming e-learning courses had significantly higher scores on extraversion than females who completed the course, but no other significant differences in the groups were found.

The results of the Independent samples' T-test, comparing the groups of males who dropped out and completed the course of computer programming e-learning (in first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration) are displayed in Table 4. Males who dropped out of computer programming e-learning courses had significantly lower scores on reward and recognition than males who completed the course, but no other significant differences were found.

H1 presumed that low initial knowledge assessment scores in computer programming e-learning play a significant role in dropout. It was presumed that withdrawers differ from non-withdrawers of computer programming e-learning courses in (H.1.1.) initial knowledge assessment scores (first evaluation of knowledge in a programming language) and performed an independent samples T-test. The results of the T-test showed that 96 participants who completed the computer programming training had higher initial knowledge assessment scores ($M = 9.84$, $SD = 3.66$) compared to those 193 participants who dropped out ($M = 8.74$, $SD = 3.47$) quickly after the assessment, $t(287) = 2.502$, $p = 0.013$.

Next, the links between dropping out and initial scores (H.1.2.) were assumed; therefore, binary logistic regression was performed to see whether initial knowledge assessment test scores predict the odds of an individual dropping out of the course. The overall model was statistically significant (Chi-squared value (1) = 6.154, $p = 0.013$), but the Nagelkerke R-squared value was 0.029. The Hosmer-Lemeshow $\chi2(8) = 7.017$, $p = 0.535$, indicating that the data fit the model well. In the logistic regression analysis, the predictor variable, the knowledge assessment test scores, were found to contribute to the model. The unstandardized Beta weight for the constant, $B = 1.509$, $SE = 0.358$, Wald = 17.739, $p < 0.001$. The unstandardized Beta weight for the predictor variable, $B=(-0.087)$, $SE = 0.035$, Wald = 6.056, $p = 0.014$. Knowledge assessment test scores were statistically significant in predicting the odds of dropping out (OR = 0.916, 95%CI [0.855, 0.982]). Withdrawers were 92% more likely to have lower initial knowledge assessment scores than non-withdrawers.

Table 2
Means, Standard Deviations, and the Pearson correlations for the study variables.

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. 1st knowledge assessment	9.278	3.58	–																
2. Individual attitude and expectation	4.643	.862	0.020	–															
3.Challenging goals	4.568	.978	0.138*	0.344***	–														
4. Clear direction	4.962	.803	0.025	0.715***	0.494***	–													
5.Reward and recognition	4.810	.991	−0.094	0.563***	0.108	0.510***	–												
6.Punishment	3.149	1.272	0.049	0.282***	0.084	0.260***	0.282***	–											
7.Social pressure and competition	3.477	1.137	0.068	0.201***	0.223***	0.232***	0.210***	0.438***	–										
8.Extraversion	3.188	.568	0.055	0.196***	0.450***	0.288***	0.102	0.029	0.241***	–									
9.Agreeable-ness	3.559	.509	−0.064	0.119*	0.271***	0.199***	0.088	0.053	0.052	0.267***	–								
10.Conscien-tiousness	3.502	.555	−0.054	0.163**	0.450***	0.253***	0.052	−0.017	0.095	0.445***	0.316***	–							
11.Negative emotionality	2.833	.764	−0.052	−0.098	−0.456***	−0.237***	0.093	0.018	−0.136*	−0.436***	−0.300***	−0.384***	–						
12.Open mindedness	3.582	.435	−0.024	0.216***	0.321***	0.258***	0.122*	−0.074	0.024	0.350***	0.138*	0.179**	−0.044	–					
13.Autonomy satisfaction	3.500	.789	0.144*	0.269***	0.533***	0.370***	0.065	0.011	0.144*	0.515***	0.221***	0.383***	−0.548***	0.241***	–				
14.Autonomy frustration	2.589	.844	−0.137*	−0.061	−0.275***	−0.125*	0.127*	0.041	0.018	−0.366***	−0.156**	−0.256***	0.436***	−0.068	−0.507***				
15.Relatedness satisfaction	4.050	.725	0.078	0.351***	0.316***	0.391***	0.186**	0.082	0.146*	0.355***	0.353***	0.221***	−0.320***	0.145*	0.464***	−0.290***	–		
16.Relatedness frustration	2.090	.836	−0.118*	−0.194***	−0.360***	−0.266***	0.001	−0.004	−0.068	−0.439***	−0.337***	−0.314***	0.417***	−0.152**	−0.430***	0.449***	−0.695***	–	
17.Competence satisfaction	3.775	.821	0.066	0.289***	0.614***	0.413***	0.098	−0.011	0.135*	0.512***	0.190***	0.468***	−0.566***	0.282***	0.691***	−0.397***	0.478***	−0.512***	–
18.Competence frustration	2.477	.983	−0.046	−0.171**	−0.472***	−0.282***	0.028	0.057	−0.052	−0.496***	−0.224***	−0.462***	0.602***	−0.192***	−0.602***	0.511***	−0.387***	0.591***	−0.731***

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3
Comparison of first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females who dropped out and completed the course of computer programming e-learning.

Logistic parameter	Completed		Dropped out		*t(175)*	*p*	*Cohen's d*
	M	*SD*	*M*	*SD*			
1st knowledge assessment	9.054	3.199	8.289	3.174	1.486	0.139	0.240
Learning motivating factors							
Individual attitude and expectation	4.727	0.721	4.785	0.743	−0.483	0.630	−0.079
Challenging goals	4.509	1.036	4.576	0.743	−0.414	0.679	−0.067
Clear direction	4.952	0.707	5.069	0.969	−1.005	0.316	−0.164
Reward and recognition	4.933	0.828	4.978	0.723	−0.309	0.758	−0.050
Punishment	3.055	1.329	3.107	0.915	−0.248	0.804	−0.040
Social pressure and competition	3.400	1.067	3.382	1.301	0.094	0.925	0.015
Personality traits							
Extraversion	3.009	0.473	3.306	0.589	−3.318	**0.001**	−0.536
Agreeableness	3.644	0.462	3.612	0.487	0.423	0.673	0.068
Conscientiousness	3.540	0.469	3.607	0.536	−0.798	0.426	−0.129
Negative emotionality	3.118	0.645	2.936	0.747	1.569	0.119	0.254
Open mindedness	3.542	0.457	3.658	0.409	−1.702	0.091	−0.275
Basic psychological needs							
Autonomy satisfaction	3.382	0.643	3.562	0.833	−1.422	0.157	−0.231
Autonomy frustration	2.600	0.784	2.506	0.852	0.693	0.489	0.113
Relatedness satisfaction	4.236	0.501	4.085	0.761	1.350	0.179	0.220
Relatedness frustration	2.036	0.740	2.103	0.917	−0.475	0.635	−0.077
Competence satisfaction	3.709	0.729	3.752	0.817	−0.334	0.739	−0.054
Competence frustration	2.555	0.888	2.548	1.048	0.043	0.966	0.007

To test H2, which assumed that the learning motivation of computer programming e-learners plays a significant role in dropout, differences between three groups were tested: those, who dropped out after the first knowledge assessment, those, who dropped out after the second knowledge assessment, and those who completed the course (H.2.1.). A one-way ANOVA was conducted to compare the effect of learning motivating factors on course completion. An analysis of variance revealed that the effect of only one motivating factor - reward and recognition on completing the course was significant, $F(2,302) = 3.013$, $p = 0.050$. A Tukey post hoc test revealed that reward and recognition as a motivator were significantly higher in those who completed the course (4.9088 ± 87173) compared to those who withdrew after the second knowledge assessment (4.3478 ± 1.29286), $p = 0.039$. However, there was no significant effect of other learning motivating factors on dropping out of computer programming e-learning courses.

A binary logistic regression analysis was conducted to investigate whether learning motivating factors predicts the odds of an individual's completing the course or dropping out of it (H.2.2). The predictor variable, reward, and recognition, in the logistic regression analysis for the whole sample and the sample of females, was found not to contribute to the model. However, in the sample

Table 4
Comparison of first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of males who dropped out and completed the course of computer programming e-learning.

Logistic parameter	Completed		Dropped out		*t(126)*	*p*	*Cohen's d*
	M	*SD*	*M*	*SD*			
1st knowledge assessment	10.763	4.016	9.933	3.759	1.118	0.266	0.216
Learning motivating factors							
Individual attitude and expectation	4.645	0.931	4.398	1.020	1.273	0.205	0.248
Challenging goals	4.684	0.914	4.535	0.998	0.788	0.433	0.153
Clear direction	5.000	0.763	4.802	0.975	1.108	0.270	0.216
Reward and recognition	4.877	0.963	4.469	1.143	1.920	**0.051**	0.374
Punishment	3.079	1.166	3.320	1.251	−1.009	0.315	−0.197
Social pressure and competition	3.447	1.086	3.660	1.103	−0.993	0.322	−0.194
Personality traits							
Extraversion	3.228	0.520	3.125	0.575	0.946	0.346	0.183
Agreeableness	3.476	0.498	3.492	0.561	−0.149	0.882	−0.029
Conscientiousness	3.329	0.558	3.427	0.605	−0.855	0.394	−0.166
Negative emotionality	2.675	0.820	2.590	0.771	0.562	0.575	0.109
Open mindedness	3.599	0.421	3.507	0.455	1.068	0.288	0.207
Basic psychological needs							
Autonomy satisfaction	3.447	0.868	3.514	0.787	−0.424	0.672	−0.082
Autonomy frustration	2.651	0.892	2.690	0.858	−0.227	0.821	−0.044
Relatedness satisfaction	4.039	0.633	3.914	0.817	0.844	0.400	0.164
Relatedness frustration	2.039	0.684	2.132	0.862	−0.587	0.558	−0.114
Competence satisfaction	3.836	0.910	3.830	0.856	0.030	0.976	0.006
Competence frustration	2.329	1.004	2.394	0.944	−0.346	0.730	−0.067

of males, the overall model was found to be statistically significant (Chi-squared value (1) = 3.882, p = 0.049), with a Nagelkerke R-squared value of 0.044. The Hosmer-Lemeshow $\chi2(7) = 7.178$, p = 0.411, indicating that the data fit the model well. The unstandardized Beta weight for the constant, B = 2.581, SE = 0.979, Wald = 6.952, p = 0.008. The unstandardized Beta weight for the predictor variable, B = −0.377, SE = 0.21, Wald = 3.518, p = 0.061, OR = 0.686, 95 % CI [0.463, 1.017].

To test H3, which assumed that personality traits of computer programming e-learners play a significant role in dropout, differences between three groups were tested: those, who drop out after the first knowledge assessment, those, who drop out after the second knowledge assessment, and those who completed the course (H.3.1.). A one-way ANOVA was conducted to compare the effect of personality traits on course completion. An analysis of variance revealed no significant effects in the whole sample and the sample of males. However, in the group of females, an analysis of variance revealed that the effect of one personality trait - extraversion on completing the course was significant, F(2,174) = 6.181, p = 0.003. A Tukey post hoc test revealed that extraversion was significantly lower in the group of females who completed the course (3.0089 ± 0.47266) in comparison to those who dropped out after the second knowledge assessment (3.5000 ± 0.52558), p = 0.007, or withdrawn after the first knowledge assessment (3.2890 ± 0.59297), p = 0.029. However, there was no significant effect of other personality traits on females' dropping out of computer programming e-learning courses.

In order to analyze the link between dropping out of computer programming e-learning courses and personality traits (H.3.2.), a binary logistic regression analysis was performed. The predictor variable, personality traits, did not contribute to the model in the logistic regression analysis for the whole sample and the sample of males. In the sample of females, the overall model was found to be statistically significant (Chi-squared value (5) = 13.724, p = 0.017), with a Nagelkerke R-squared value of 0.105. The Hosmer-Lemeshow $\chi2(8) = 5.547$, p = 0.698, indicating that the data fit the model well. The unstandardized Beta weight for the predictor variable extraversion, B = 0.996, SE = 0.392, Wald = 6.439, p = 0.011. Females' extraversion was statistically significant in predicting the odds of dropping out, OR = 2.706 95 % CI [1.254, 5.839]. Withdrawers were almost three times more likely to have higher extraversion than non-withdrawers.

To test H4, which assumed that satisfaction/frustration of basic psychological needs of computer programming e-learners plays a significant role in dropout, firstly it was tested whether withdrawers differ from non-withdrawers of computer programming e-learning courses in (H.4.1.) satisfaction/frustration of basic psychological needs. A one-way ANOVA was conducted to compare the effect of basic psychological needs satisfaction/frustration on course completion. An analysis of variance revealed that the effect of only one factor – relatedness frustration on dropping out of the course was significant, F(2,302) = 4.016, p = 0.019. A Tukey post hoc test revealed that relatedness frustration was significantly higher in those who dropped out of the course after the first knowledge assessment (2.1694 ± 0.90730) compared to those who withdrew after the second knowledge assessment (1.6771 ± 0.57332), p = 0.018. However, there was no significant effect of other psychological needs satisfaction/frustration on dropping out of computer programming e-learning courses.

Next, the links between dropping out and satisfaction/frustration of basic psychological needs (H.4.2.) were assumed. Therefore, a binary logistic regression analysis was conducted to investigate whether satisfaction/frustration of basic psychological needs predicts

Table 5
Comparison of first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females (n = 121) and males (n = 88) who dropped out of the course of computer programming e-learning.

Logistic parameter	Females		Males		*t(209)*	*p*	Mean Difference	Standard Error Difference	*Cohen's d*	95 % CI for Cohen's d	
	M	*SD*	*M*	*SD*						Lower	Upper
1st knowledge assessment	8.289	3.174	9.933	3.759	**3.438**	**<0.001**	1.644	0.478	0.479	0.201	0.755
Learning motivating factors											
Individual attitude and expectation	4.785	0.743	4.398	1.020	**−3.157**	**0.002**	−0.387	0.123	−0.445	−0.725	−0.165
Challenging goals	4.576	0.743	4.535	0.998	−0.295	0.768	−0.041	0.138	−0.042	−0.318	0.235
Clear direction	5.069	0.969	4.802	0.975	**−2.260**	**0.025**	−0.267	0.118	−0.319	−0.596	−0.040
Reward and recognition	4.978	0.723	4.469	1.143	**−3.554**	**<0.001**	−0.509	0.143	−0.501	−0.781	−0.220
Punishment	3.107	0.915	3.320	1.251	1.176	0.241	0.212	0.181	0.166	−0.111	0.443
Social pressure and competition	3.382	1.301	3.660	1.103	1.689	0.093	0.278	0.164	0.238	−0.039	0.515
Personality traits											
Extraversion	3.306	0.589	3.125	0.575	**−2.224**	**0.027**	−0.181	0.081	−0.311	−0.585	−0.035
Agreeableness	3.612	0.487	3.492	0.561	−1.653	0.100	−0.120	0.073	−0.231	−0.505	0.044
Conscientiousness	3.607	0.536	3.427	0.605	**−2.273**	**0.024**	−0.180	0.079	−0.317	−0.592	−0.042
Negative emotionality	2.936	0.747	2.590	0.771	**−3.274**	**0.001**	−0.346	0.106	−0.457	−0.734	−0.179
Open mindedness	3.658	0.409	3.507	0.455	**−2.536**	**0.012**	−0.152	0.060	−0.354	−0.630	−0.078
Basic psychological needs											
Autonomy satisfaction	3.562	0.833	3.514	0.787	−0.416	0.678	−0.048	0.114	−0.058	−0.334	0.217
Autonomy frustration	2.506	0.852	2.690	0.858	1.527	0.128	0.183	0.120	0.215	−0.062	0.491
Relatedness satisfaction	4.085	0.761	3.914	0.817	−1.550	0.123	−0.171	0.110	−0.218	−0.494	0.059
Relatedness frustration	2.103	0.917	2.132	0.862	0.230	0.819	0.029	0.126	0.032	−0.243	0.308
Competence satisfaction	3.752	0.817	3.830	0.856	0.669	0.504	0.078	0.117	0.094	−0.182	0.370
Competence frustration	2.548	1.048	2.394	0.944	−1.088	0.278	−0.154	0.141	−0.153	−0.429	0.123

the odds of an individual's completing the course or dropping out of it. In the logistic regression analysis for the whole sample, the predictor variable, satisfaction/frustration of basic psychological needs was found not to contribute to the model. The overall model in the group of males was statistically significant but with a Nagelkerke R-squared value of 0.038. The Hosmer-Lemeshow $\chi2(8) = 10.011$, $p = 0.264$, indicating that the data fit the model well. Out of six predictor variables, two variables significantly contributed to the model: autonomy satisfaction and relatedness satisfaction. The unstandardized Beta weight for the predictor variable, autonomy satisfaction, $B = 0.516$, $SE = 0.249$, Wald = 4.301, $p = 0.038$, $OR = 1.675$ 95 % CI [1.029, 2.727]. The unstandardized Beta weight for the predictor variable, relatedness satisfaction, $B = -0.540$, $SE = 0.267$, Wald = 4.081, $p = 0.043$, $OR = 0.583$ 95 % CI [0.345, 0.984].

Lastly, we hypothesized that gender plays a significant role in completing the course or dropping out of it (H.5). Independent samples T-test was performed to identify differences in first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females and males who dropped out of the course of computer programming e-learning (H.5.1). The Independent samples T-test results comparing first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females ($n = 121$) and males ($n = 88$) who dropped out of the course of computer programming e-learning are displayed in Table 5.

The analysis in the group of dropouts (Table 5 and Fig. 1) revealed that males had significantly higher scores in the first knowledge assessment ($M = 9.933$, $SD = 3.759$) than females ($M = 8.289$, $SD = 3.174$), and they also had higher scores in open-mindedness ($M =$

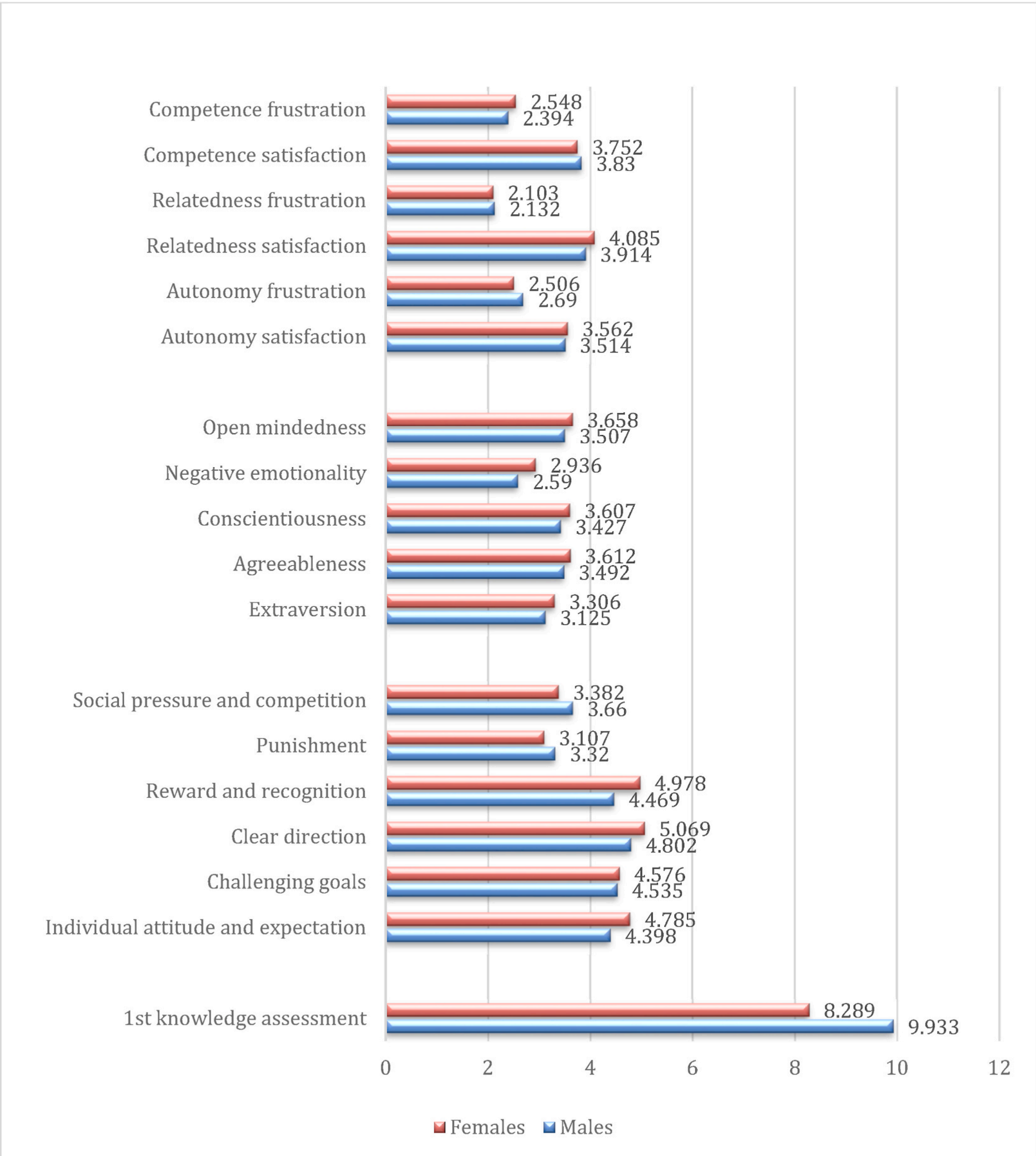

Fig. 1. Comparison of dropouts' females and males.

Table 6
Comparison of first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females (n = 56) and males (n = 38) who completed the course of computer programming e-learning.

Logistic parameter	Females		Males		*t(92)*	*p*	Mean Difference	Standard Error Difference	*Cohen's d*	95 % CI for Cohen's d	
	M	*SD*	*M*	*SD*						Lower	Upper
1st knowledge assessment	9.054	3.199	10.763	4.016	**2.291**	**0.024**	1.710	0.746	0.482	0.062	0.898
Learning motivating factors											
Individual attitude and expectation	4.727	0.721	4.645	0.931	−0.481	0.631	−0.083	0.171	−0.102	−0.515	0.312
Challenging goals	4.509	1.036	4.684	0.914	0.840	0.403	0.175	0.208	0.177	−0.237	0.591
Clear direction	4.952	0.707	5.000	0.763	0.315	0.754	0.048	0.154	0.066	−0.347	0.480
Reward and recognition	4.933	0.828	4.877	0.963	−0.301	0.764	−0.056	0.187	−0.063	−0.477	0.350
Punishment	3.055	1.329	3.079	1.166	0.091	0.927	0.024	0.267	0.019	−0.394	0.433
Social pressure and competition	3.400	1.067	3.447	1.086	0.209	0.835	0.047	0.227	0.044	−0.370	0.457
Personality traits											
Extraversion	3.009	0.473	3.228	0.520	**2.117**	**0.037**	0.219	0.103	0.445	0.027	0.861
Agreeableness	3.644	0.462	3.476	0.498	−1.681	0.096	−0.168	0.100	−0.353	−0.767	0.063
Conscientiousness	3.540	0.469	3.329	0.558	**−1.983**	**0.050**	−0.211	0.107	−0.417	−0.832	6.846e-4
Negative emotionality	3.118	0.645	2.675	0.820	**−2.919**	**0.004**	−0.442	0.151	−0.614	−1.033	−0.191
Open mindedness	3.542	0.457	3.599	0.421	0.612	0.542	0.057	0.093	0.129	−0.284	0.541
Basic psychological needs											
Autonomy satisfaction	3.382	0.643	3.447	0.868	0.418	0.677	0.066	0.157	0.088	−0.326	0.502
Autonomy frustration	2.600	0.784	2.651	0.892	0.293	0.770	0.051	0.175	0.062	−0.352	0.475
Relatedness satisfaction	4.236	0.501	4.039	0.633	−1.672	0.098	−0.197	0.118	−0.353	−0.768	0.065
Relatedness frustration	2.036	0.740	2.039	0.684	0.021	0.984	0.003	0.151	0.004	−0.409	0.418
Competence satisfaction	3.709	0.729	3.836	0.910	0.742	0.460	0.126	0.170	0.157	−0.258	0.570
Competence frustration	2.555	0.888	2.329	1.004	−1.142	0.257	−0.226	0.198	−0.241	−0.655	0.175

3.507, SD = 0.455) in comparison to females (M = 2.936, SD = 0.747). Females demonstrated significantly higher scores in individual attitude and expectation (M = 4.785, SD = 0.743) in comparison to males (M = 4.398, SD = 1.020), and they also had higher scores in clear direction (M = 5.069, SD = 0.723) than males (M = 4.802, SD = 0.975) and reward and recognition (M = 4.978, SD = 0.915) to compare to males (M = 4.469, SD = 1.143). Females who dropped out also demonstrated significantly higher extraversion (M = 3.306, SD = 0.589) than males (M = 3.125, SD = 0.575), also higher conscientiousness (M = 3.607, SD = 0.536) than males (M = 3.427, SD = 0.605), and negative emotionality (M = 2.936, SD = 0.747) in comparison to males (M = 2.590, SD = 0.771). No significant differences between groups of females and males were found in other study variables.

Afterward, the independent samples T-test was performed to identify differences in first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females and males who completed the course of computer programming e-learning (H.5.2). The results of the T-test, comparing first knowledge assessment grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in groups of females and males who completed the course, are presented in Table 6.

The analysis in the group of participants who completed the computer programming e-learning course (Table 6 and Fig. 2) revealed that males had significantly higher scores in the first knowledge assessment (M = 10.763, SD = 4.016) than females (M = 9.054, SD = 3.199), and they also had higher scores in extraversion (M = 3.228, SD = 0.520) in comparison to females (M = 3.009, SD = 0.473). Females who completed the course demonstrated significantly higher scores in conscientiousness (M = 3.644, SD = 0.462) in

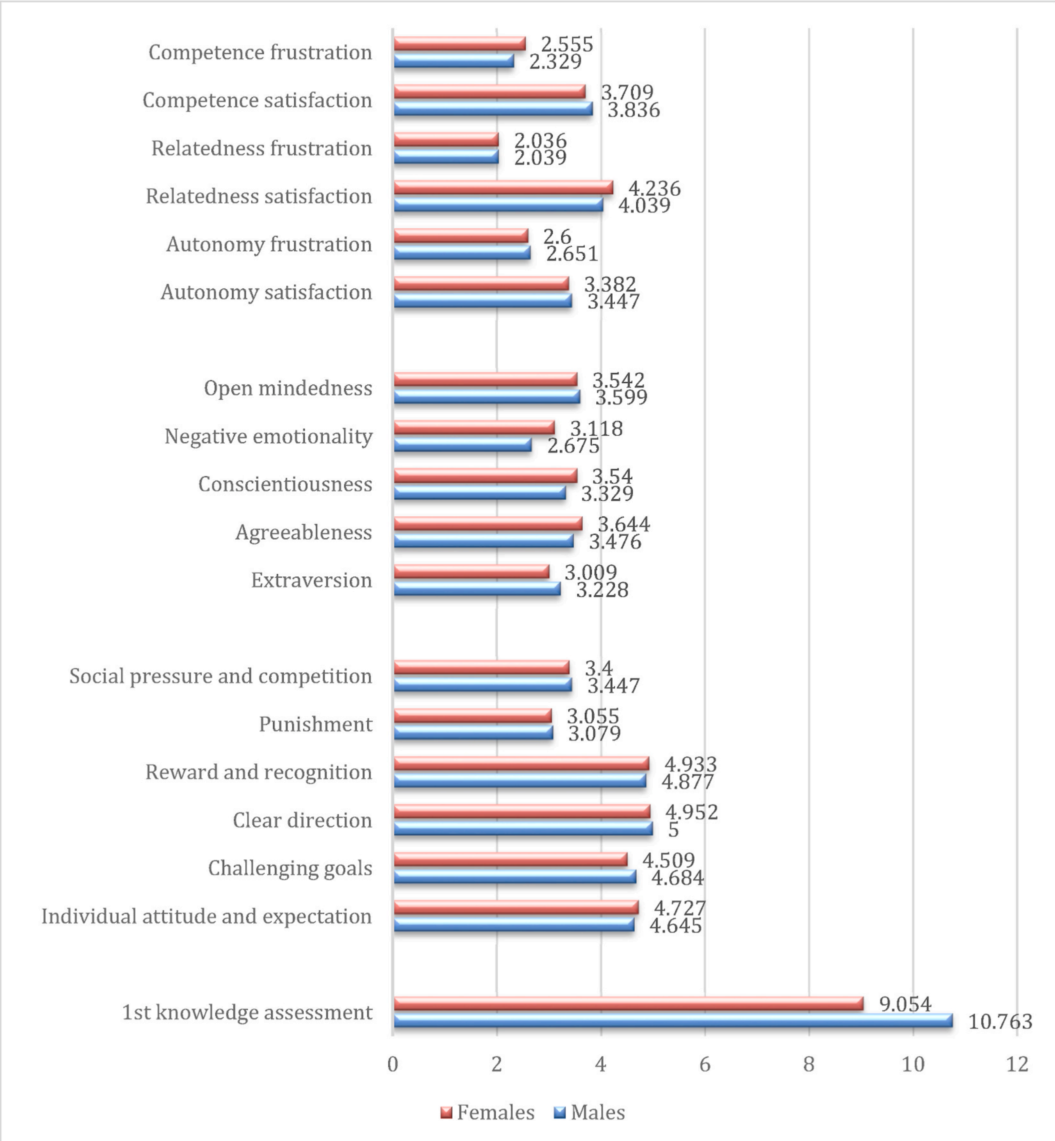

Fig. 2. Comparison of females and males who completed the course.

comparison to males (M = 3.476, SD = 0.498), but they also had higher scores in negative emotionality (M = 3.118, SD = 0.645) than males (M = 2.675, SD = 0.820). No significant differences between groups of females and males were found in other study variables.

4. Discussion

This study was probably the first to explore the effect of initial grades, learning motivating factors, personality traits, and basic psychological needs satisfaction/frustration in completing the course of computer programming e-learning or dropping out of it. It expands knowledge on psychological factors contributing to completing the course in computer programming e-learning or dropping out of it. It was relevant to analyze these factors, as computer programming skills are essential skills that future professionals must possess. Previous studies have reported that acquiring these skills is challenging and might result in high dropout rates.

Several studies have demonstrated the impact of some of the abovementioned characteristics on dropouts at secondary or higher education levels. However, self-directed e-learning was examined for the first time.

The theoretical framework was based on four conceptual models: the frustration-self-esteem model, proposed by Finn [25]; the learning motivating factors model, proposed by Law et al. [43]; the personality traits model, proposed by Soto & John [58], and basic psychological needs model, proposed by Ryan & Deci [62].

As hypothesized (H1), this study confirmed that low initial knowledge assessment scores in computer programming e-learning play a significant role in dropout. As Finn [25] proposed, low accomplishment lowers a learner's self-esteem, increasing the likelihood of dropping out. This study did not focus on self-esteem directly, but it found that participants who completed the computer programming e-learning courses had higher initial knowledge assessment scores than those who dropped out quickly after the first assessment. Presumably, those who received lower grades also experienced self-esteem frustration, contributing to the decision to drop out. Next, knowledge assessment test scores were found to be statistically significant in predicting the odds of dropping out, and withdrawers were 92% more likely to have lower initial knowledge assessment scores than non-withdrawers. So this study adds to previous surveys, which found that most dropouts occur during the early stages of learning [29], and confirms that initial achievements contribute to successful completion. However, this study only non-directly supports the premise that learners' achievement frustration might diminish self-esteem and self-efficacy, while self-efficacy and self-esteem are significant predictors of dropouts [16,30,31]. Therefore, the conceptual model still needs verification, applying the constructs of self-esteem and self-efficacy directly for computer programming e-learners.

Furthermore, this study intended to clarify the learning motivating factors related to dropping out or completing the course of computer programming e-learning. It was hypothesized (H2) that the learning motivation of computer programming e-learners plays a significant role in dropout. According to previous studies, learning motivation is a critical component in determining learning outcomes because motivated learners put in more effort, are more attentive, and are more persistent in the face of problems, whereas unmotivated learners are more likely to drop out [32,47,48]. This study explored six learning motivating factors proposed by Law et al. [43]: individual attitude and expectation, challenging goals, clear direction, reward and recognition, punishment, social pressure, and competition. Differences between three groups were tested: those, who dropped out after the first knowledge assessment, those, who dropped out after the second knowledge assessment, and those who completed the course. An analysis of variance revealed that the effect of only one motivating factor - reward and recognition on completing the course was significant. Reward and recognition as a motivator were significantly higher in those who completed the course compared to those who dropped out after the second knowledge assessment. However, there was no significant effect of other learning motivating factors on dropping out of computer programming e-learning courses.

Males completing the computer programming e-learning course were almost 70% likelier to have higher reward and recognition motivation than those who dropped out. Reward and recognition were statistically significant in predicting the odds of dropping out in the group of males but not in the group of females or the whole sample. These findings raise more questions than provide answers. Previous surveys suggested explicit links between dropping out and learning motivation, but most studies proposed that intrinsic learning motivation significantly reduces dropout, while extrinsic motivation's effect was blurred [46]. In this study, extrinsic motivation was found to contribute to the males' completion of the course in computer programming e-learning.

Moreover, in the groups of females, no significant effects of learning motivating factors on dropping out or completing the course were found, and it might imply that other instruments could be applied to assess learners' e-learning motivation or that corrections in the research design must be introduced. The hypothesis that the learning motivation of computer programming e-learners plays a significant role in dropout was partly confirmed, but the findings need further investigation.

This study also hypothesized that (H3) personality traits of computer programming e-learners play a significant role in dropout. This presumption was based on previous research which found that personal characteristics could affect retention [46], or revealed that each personality trait can differently impact the intention to persevere in online learning and not drop out [59]. Previous studies confirmed that agreeableness, extraversion, and conscientiousness play a significant positive role in the intention to continue learning [60], while the effect of neuroticism on online learning completion is negative. Surprisingly, in this study, an analysis of variance revealed no significant effects of personality traits in the whole sample and the sample of males. In the group of females, an analysis of variance revealed that the effect of one personality trait - extraversion on completing the course was significant: extraversion was significantly lower in the group of females who completed the course in comparison to those who dropped after the second knowledge assessment or after the first knowledge assessment test. Personality traits, the predictor variable in the logistic regression analysis for the whole sample and the sample of males, was found to not contribute to the model. However, females' extraversion was statistically significant in predicting the odds of dropping out: withdrawers were almost three times more likely to have higher extraversion than non-withdrawers. These results could partly be explained based on the description of extraversion in the Big Five model. Extraversion is described as a combination of sociability (a person is outgoing and sociable), assertiveness (a person is dominant, assertive, having an impact on others), and energy level (a person is full of energy and excitement) [58]. Computer programing e-learning requires good concentration skills, and previous studies reported high introversion in computer programming e-learners [63]. However, this study partly confirmed the hypothesis that personality traits of computer programming e-learners play a significant role in dropout, and the factors relating to personality traits and dropping out of computer programing courses in both groups of females and males still need clarification.

Next, in this research, it was hypothesized that (H4) satisfaction/frustration of basic psychological needs of computer programming e-learners play a significant role in dropout. This assumption was based on previous studies reporting the indirect importance of learners' basic psychological needs satisfaction or frustration for dropouts [61] and studies indicating different importance of needs in the study process [56]. This research raised the question of whether satisfaction/frustration of the need for competence is more critical than the need for relatedness and how satisfaction/frustration of basic psychological needs contribute to learning continuation or dropping out. Surprisingly, the findings do not fully support some previous results, which revealed that students with a preference for systematic planning and an intellectual understanding of a situation (need for competence) are more likely to succeed than students preferring concrete experience and interaction (need for relatedness) with other students [56]. An analysis of variance revealed that the effect of relatedness frustration on dropping out of the course was significant: relatedness frustration was significantly higher in those who dropped out of the course after the first knowledge assessment compared to those who withdrew after the second knowledge assessment. A binary logistic regression analysis revealed that autonomy and relatedness satisfaction might also predict the odds of an individual's completing the course or dropping out of it in the group of males. However, these results apply just to a tiny percentage of the male participants' sample, so these results should be taken with caution and would be preferably omitted from further discussion. Overall, this study has partly confirmed that satisfaction/frustration of basic psychological needs of computer programming e-learners plays a significant role in dropout. However, the impact of satisfaction/frustration of basic psychological needs in both groups of females and males on completing the computer programming e-learning course is still ambiguous.

Finally, this study also hypothesized (H5) that gender plays a significant role in completing the course of computer programming e-learning or dropping out of it. The presumption was based on previous studies which reported that the dropout rate of females is much lower than that of males, and males face a higher risk of dropping out [65]. Additionally, previous studies found that male dropouts relate to negative learners' attitudes [33], and the factors adding to dropouts in groups of females and males are comparatively distinct [66]. In this study, profiles of females and males in the group of dropouts and in the group of those who completed the course were analyzed. The findings revealed that in the group of dropouts, males had significantly higher scores in the first knowledge assessment and higher scores in open-mindedness compared to females. Females demonstrated significantly higher scores in individual attitude and expectation, clear direction, and reward and recognition than males. Females who dropped out also demonstrated significantly higher extraversion, conscientiousness, and negative emotionality. No significant differences between groups of females and males were found in other study variables. In those who completed the course of computer programming e-learning, males demonstrated higher scores in the first knowledge assessment and extraversion than females. Females who completed the course demonstrated significantly higher scores in conscientiousness, but they also had higher scores in negative emotionality than males, but no significant differences between groups of females and males were found in other study variables.

Many variables need to be considered in learning analytics to predict student behavior in a course or a program, such as knowledge and skills in the domain, engagement, motivation, anxiety, student demographic characteristics, past academic history, academic performance, self-efficacy, satisfaction [73]. This study, which combined educational and psychological approaches, adds to the literature on predictive dropout models in computer programming e-learning environments, although predictive models in self-paced learning have many limitations [74].

Overall, the results of this study, performed in a computer programming e-learning platform, give some insights for testing the findings in other learning environments. Mentors and learners can benefit from the results of this study by getting insights into the risks caused by various factors and possibilities of prevention.

4.1. Limitations

This study has several significant limitations. First, the dropout rates were higher than it was expected, so the opportunity to apply the structural equation modeling (SEM) was lost, as the minimum sample size for SEM is preferably not less than 150–200 participants in a group [68]. Multigroup SEM would clarify the associations between the study variables; thus, it is strongly recommended to ensure a sufficient sample size in future quasi-experiments.

Next, the measure that was chosento explore learners' learning motivation revealed some thought-provoking information regarding learning motivating factors. However, this information is insufficient to clarify the learning motivation of computer programming e-learners, and adding additional instruments to evaluate learning motivation in future research are recommended.

Next, this study was conducted in Lithuania; all participants were Lithuanians. Therefore, the results of this study would not preferably be generalized, as they might reflect cultural specifics and the context of this country. In order to conclude that extrovert females would drop out of computer programming e-learning courses, that reward and recognition significantly motivate e-learners, or that relatedness frustration adds negatively to the completion of the course in computer programming e-learning, a similar quasi-experiment should be repeated in different countries, preferably revealing peculiarities of factors contributing to the successful completion of the programming courses in different European, American, and Asian regions.

Fourth, applying a corrected research design in future research is recommended. In this study, psychological parameters were firstly measured, and then the learning process was started. However, in future research, it would be recommended to measure personality traits first and then relate basic psychological needs satisfaction/frustration, and learning motivation to the learning process. We would specifically explore whether the learners' needs for autonomy, competence, and relatedness are satisfied/frustrated as they study this course, and we would also ask what motivates them to learn in this specific course.

Fifth, teacher or peer feedback is essential in e-learning and should be considered as a significant factor in dropout research. The support and feedback that the learners of this e-course were provided with were analyzed in another scientific article produced by the authors of this paper.

To sum up, even though this study added to a better understanding of factors contributing to the completion or dropping out of computer programming e-learning courses, the findings should be regarded with caution due to significant limitations. Given the sampling strategy, studies should continue in other programs and contexts, in order to validate the results.

5. Conclusions

The present study addressed the role of initial grades (achievements), personality traits, learning motivation, and satisfaction/frustration of basic psychological needs in dropping out of a computer programming e-learning course. It expanded knowledge on psychological factors contributing to completing the course in computer programming e-learning or dropping out of it.

1) Low initial knowledge assessment scores in computer programming e-learning play a significant role in dropout. It was found that participants who completed the computer programming e-learning courses had higher initial knowledge assessment scores compared to those participants who dropped out quickly after the first assessment.
2) Reward and recognition as motivators play significant roles in the dropout of computer programming e-learners. Reward and recognition as motivators were significantly higher in those who completed the course than those who dropped out after the second knowledge assessment. Reward and recognition were statistically significant in predicting the odds of dropping out in the group of males but not in the group of females or the whole sample.
3) Personality traits of computer programming e-learners play a significant role in dropout: females' extraversion was found to be statistically significant in predicting the odds of dropping out. Extraversion was significantly lower in females who completed the course compared to those who dropped after the second knowledge assessment or after the first knowledge assessment test. Withdrawers were almost three times more likely to have higher extraversion than non-withdrawers.
4) Satisfaction/frustration of basic psychological needs of computer programming e-learners plays a significant role in dropout. Relatedness frustration plays a significant role in the dropout of computer programming e-learning: relatedness frustration was significantly higher among those who dropped out of the course after the first knowledge assessment than those who withdrew after the second knowledge assessment. However, the impact of satisfaction/frustration of basic psychological needs separately in groups of females and males on completing the computer programming e-learning course is still ambiguous.
5) Gender plays a significant role in completing the course of computer programming e-learning or dropping out of it: reward and recognition are more important to males than females. In the group of dropouts, males had significantly higher scores in the first knowledge assessment and higher scores in open-mindedness compared to females, while females demonstrated significantly higher scores in individual attitude and expectation, clear direction, and reward and recognition to males. Females who dropped out also demonstrated significantly higher extraversion, conscientiousness, and negative emotionality. In those who completed the course of computer programming e-learning, males demonstrated higher scores in the first knowledge assessment and extraversion than females. Females who completed the course demonstrated significantly higher scores in conscientiousness, but they also had higher scores in negative emotionality than males, and no significant differences between groups of females and males were found in other study variables.

Due to significant limitations of the sample size, cultural context, measures applied, and research design, the findings would preferably be regarded with caution.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Aiste Dirzyte: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Aidas Perminas:** Conceptualization, Investigation. **Lukas Kaminskis:** Funding acquisition, Resources, Software. **Giedrius Žebrauskas:** Software, Validation. **Živilė Sederevičiūtė – Pačiauskienė:** Investigation, Writing – original draft, Writing – review & editing. **Jolita Šliogerienė:** Writing – original draft, Writing – review & editing. **Jelena Suchanova:** Data curation, Writing – review & editing. **Romualda Rimašiūtė – Knabikienė:** Conceptualization, Formal analysis, Methodology. **Aleksandras Patapas:** Investigation, Writing – review & editing. **Indre Gajdosikiene:** Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Dirzyte Aiste, Perminas Aidas, Kaminskis Lukas, Zebrauskas Giedrius, Sedereviciute - Paciauskiene Zivile, Sliogeriene Jolita, Suchanova Jelena reports financial support was provided by Public Institution Lithuanian Business Support Agency. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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