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Personality and satisfaction with online courses: The relation between the Big Five personality traits and satisfaction with online learning activities

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Abstract

Online courses have become widespread in higher education. Yet, despite their prevalence, they may not suit all learners. Personality influences learner satisfaction and therefore affects learning experience. This study explores the relation between personality traits (using Costa & McCare's Big-Five model) and student satisfaction with various of learning activities offered in online courses, called Techno-Pedagogical Learning Solutions (TPLS). The tested TPLS were discussion groups, digital books, online assignments, surveys/polls and media. Questionnaires were used to measure personality types and satisfaction of 108 university students enrolled in a credited online academic course. Significant correlations were found between all five personality traits and satisfaction with several TPLS. Cluster analysis method was applied to identify learners with similar personality traits. Four groups were formed and group's satisfaction score was measured. It was found that learners assigned to the "neurotic" group exhibited low satisfaction with all TPLS, contrary to learners assigned to the "non-neurotic" group. The findings clearly indicate that personality plays a significant role in online learner satisfaction. Thus, personality traits should be considered when designing learning activities for online courses. Such personality-based personalization may ensure that no learner is left behind, regardless of his\ her attitude toward online learning.

Keywords Distance education · Online learning activities · Online courses · Personality traits · Personalization · Higher education

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1 Introduction

Online courses have become prevalent in higher education (Allen & Seaman, 2017; Cohen & Baruth, 2017; Lowenthal et al., 2019; Siddiquei & Khalid, 2018; Soffer & Nachmias, 2018), especially due to social distancing requirements caused by the COVID-19 pandemic (Altbach & De Wit, 2020; Baruth et al., 2021). Online learning can occur anytime and anywhere, in different environments and using various modern educational techniques (Bourkoukou & El Bachari, 2016; Evirgen & Çengel, 2012; Halawa et al., 2015; Lee & Lee, 2006; Soles & Moller, 2001; Sun et al., 2008). Yet, online learning is not free of limitations and may not suit all learners (Ezra et al., 2021; Sahinidis & Tsaknis, 2020; Santo, 2001). Basic infrastructure conditions and certain technological skills are required to learn online. Additionally, students may need organizational capabilities, extra motivation and self-discipline to success in their online learning experience (Jacob & Radhai, 2016). Another significant issue is the impairment of interpersonal relationships (Davis et al., 2019), as the lack of physical communication damages social interactions (Bolliger & Erichsen, 2013; Tayebinik & Puteh, 2012), and allows less personalized attention from the instructor (compared to traditional learning) (Jacob & Radhai, 2016). Therefore, while online learning is gaining momentum, some learners find it very difficult to connect to it (Santo, 2001). Particularly in view of learner diversity, the growth of online learning raises the following question: Does online learning as it is currently offered meet the needs of each learner? The answer to this question is complex and will likely often be negative. Fortunately, today's technology facilitates personalization by offering tailored learning platforms (El Bachari et al., 2010), using variety of online learning activities.

Personality has been found to affect learner satisfaction (Bolliger & Erichsen, 2013; Shih et al., 2013), including in distance learning environments (Bolliger & Erichsen, 2013; Daughenbaugh, Daughenbaugh, et al., 2002; Daughenbaugh, Ensminger, et al., 2002; Soles & Moller, 2001). Therefore, personality exerts an important impact on the effectiveness of the learning process and plays a major role in both teaching and learning (Fatahi et al., 2009). Learners react differently to different learning methods, depending on their personality traits (Irani et al., 2003; Kokkinos et al., 2015). A better understanding of the role of personality can lead to a greater appreciation of learning needs, as well as assist educators in ensuring that an optimal learning environment is provided (Kim et al., 2013; Wicklein & Rojewski, 1995). Hence, a personality type classification is needed to adapt learning to learners' individual personalities. One such classification is the Big Five model (Costa & McCrae, 1985), considered the most common modern psychological model for characterizing human personality (Cohen & Baruth, 2017; Franic et al., 2014; Ghorbani & Montazer, 2015; Gosling et al., 2003; Li & Armstrong, 2015; Papamitsiou & Economides, 2014; Sorić et al., 2017; Soto & John, 2017; Tlili et al., 2019a, 2019b).

Measuring student satisfaction has become a "hot topic" in higher education research (Horzum, 2015; Sahinidis & Tsaknis, 2020). Some studies have found that interactions in online learning environments are highly correlated with student satisfaction (Dziuban et al., 2015). Indeed, some researchers even claim that if students are dissatisfied with their online experience, they may not return for more (Soles & Moller, 2001). In addition, it seems that personality-based tailored courses positively affect learner satisfaction (Denphaisarn, 2014; Komarraju & Karau, 2005), since different personalities require different learning solutions (Bachari et al., 2012). Hence, online courses should be tailored to offer appropriate Techno-Pedagogical Learning Solutions (TPLS) for each personality type. In this study the term Techno-Pedagogical Learning Solutions refers to a variety of pedagogical activities offered through technological tools. Indeed, the online platform makes it possible to use a wide range of technological tools to advance learning (Keengwe & Kidd, 2010; Moore et al., 2011). Despite the above claims, the relationship between personality and online learning satisfaction is still an emerging topic (Downs, 2019). Not much research has examined learning design according to personality types. Moreover, the role of learners' personalities in online learning systems has also not received sufficient research attention (Tlili et al., 2019a, 2019b). There are relatively few studies in which designers take personality traits into account (Bishop-Clark et al., 2007; Chen & Lin, 2017; Kim et al., 2013). To the best of our knowledge, there is no empirical evidence in the literature confirming the connection between the Big Five personality traits and learner satisfaction with the examined TPLS. The present study aims to shed a light on that matter and to find evidence for this connection, so that personality traits will be taken into account during the design process of online courses.

In the current study, self-report questionnaires were distributed in order to find significant correlations between the Big Five personality types and satisfaction level with each of the examined TPLS. In addition, k-means cluster analysis was used to characterize groups of students based on their personality traits to find the most satisfying TPLS for each cluster.

Personality-based personalization is a growing trend (Lee & Ferwerda, 2017) that may facilitate the creation of more effective learning processes (Ghorbani & Montazer, 2015). The current study seeks to propose a model for personality based personalized learning paths. The findings of this study will make it possible to design different learning paths based on the most satisfying TPLS for each type of student, such that learners can choose their preferred path. This proposed personalization has the potential to increase learner satisfaction with online courses and thus benefit the entire field of online learning design. Personality-based personalization can help in designing improved online courses, such that no learners are left behind, regardless of their attitude toward online learning. The few studies that discussed these connections did not test them empirically (Harrington & Loffredo, 2010; Kim et al., 2013; Soles & Moller, 2001). Our study bridges this gap between theory and practice. Learning that can be adapted to the needs of each individual learner can make it possible to appeal to a wider audience from different socioeconomic backgrounds, even at times of crisis such as the COVID-19 outbreak (Dhawan, 2020).

2 Literature review

2.1 Personality and the Big Five model

Personality type can optimally characterize interpersonal differences (Fatahi et al., 2016; Irani et al., 2003; Tlili et al., 2017). Several models have been proposed for understanding personality (Tlili et al., 2016). Among these, the Big Five model (Costa & McCrae, 1985) is the most common and recognizable modern psychological model (Franic et al., 2014; Ghorbani & Montazer, 2015; Gosling et al., 2003; Li & Armstrong, 2015; Papamitsiou & Economides, 2014; Sorić et al., 2017; Soto & John, 2017; Tlili et al., 2019a, 2019b) and has been increasingly studied and validated in the scientific literature (Papamitsiou & Economides, 2014). The Big Five model, generates a taxonomy that characterizes people by emphasizing the dimensions that distinguish them (Gosling et al., 2003) in a way that crosses cultures and gender (Wu & Lai, 2019) and takes into account the complexity of the human personality (Caspi et al., 2006; Danesh & Mortazavi, 2010; Moharib Al-Otaibi, 2012).

The Big Five personality dimensions are: *Extraversion* – a combination of interpersonal interaction skills, positive influence, and energy level; *Agreeableness* – the way in which an individual communicates with the environment; *Conscientiousness* – the ability to control impulses, be organized and motivated; *Openness to Experience* – an individual's interest in new experiences or ideas; *Neuroticism* – an individual's degree of emotional stability (Patrick, 2011). Each individual's personality structure places him or her at a different point along the dimension spectrum, thus reflecting interpersonal differences (Cohen & Baruth, 2017). People with high Extraversion scores are friendly, warm, social, extroverted, energetic, ambitious, confident and enthusiastic, and seek stimulation through communication and conversation with others. Those with high Agreeableness scores are trustful, altruistic, cooperative, and modest. They demonstrate sympathy and concern for the needs of others and usually avoid conflicts. People with high Conscientiousness scores are organized, reliable, self-disciplined, decent, attentive and persistent. Those with high scores on the Openness to Experience dimension are unpredictable, take risks, have difficulty concentrating and appreciate the importance of spiritual and artistic quests. People with high scores on the Neuroticism dimension are sensitive and usually demonstrate negative feelings such as anger, stress and depression, whereas those with low Neuroticism scores are characterized as emotionally stable and usually described as calm, stable, mature, and resilient (Sahinidis & Tsaknis, 2020).

Personality traits appear to affect students' learning behaviors, which in turn determine their learning preferences (Kim et al., 2013; Soles & Moller, 2001). In examining the relationship between students' personality types and their success in online courses, Meredith (2011) found that personality is an influencing factor in student success as measured by final course grade and retention rate. Personality influences how learners handle different learning tasks (Kokkinos et al., 2015). Hence, a better understanding of personality can lead to a greater appreciation of learning needs, as well as assist educators in providing an optimal learning environment (Kim et al., 2013; Wicklein & Rojewski, 1995). The Big Five model appears to be the most prevalent personality indicator within the broad research scope of personality-learning relations (Mcilroy et al., 2016). Its simplicity and comprehensiveness may explain its widespread use (Fatahi et al., 2016). Nevertheless, we must also mention the opposing view, which claims that personality traits are unstable and therefore cannot constitute a significant factor in learning design (Kim et al., 2013).

2.2 Fully online courses and Techno-Pedagogical Learning Solutions (TPLS)

Internet availability has increased the demand for online learning. Consequently, online learning has gained momentum (Hameed et al., 2008; Tayebinik & Puteh, 2012) and is growing at an astonishing rate (Bettinger et al., 2017; Bishop-Clark et al., 2007; Kauffman, 2015). Moreover, the availability of high-speed Internet on mobile devices has facilitated the expansion of online education services (Krasnov et al., 2018). Online learning has become particularly prevalent in higher education (Bolliger & Erichsen, 2013; Park & Choi, 2009; Regan et al., 2012; Soffer & Nachmias, 2018; Tlili et al., 2016), especially during the COVID-19 outbreak, which forced universities and colleges around the world to close their campuses and shift to distance education to enable students to complete their studies (Altbach & De Wit, 2020; Auothors et al., 2021a). Hence, we have been witness to a rise in the number of accredited courses offered online (Soffer & Nachmias, 2018). These courses deliver 80% or more of their content via the internet (Allen et al., 2016; Simonson & Smaldino, 2014) and generally do not require face-to-face meetings (Allen et al., 2016; Bolliger & Erichsen, 2013). Moreover, other types of online courses such as MOOCs (Massive Open Online Courses) are free, and anyone with an internet connection can enroll in them (Weinhardt & Sitzmann, 2019).

Despite the promise of cost savings (Bettinger et al., 2017), it should be noted that online learning is not free of limitations and may not be suitable for all learners (Sahinidis & Tsaknis, 2020). Therefore, while online learning is gaining momentum, some learners find it very difficult to adjust to it (Santo, 2001). In order to study online, learners require certain technical skills and basic infrastructure. Additionally, for students to have a successful online learning experience, they may also need organizational abilities, extra motivation, and self-discipline (Jacob & Radhai, 2016). Another significant issue is that online learning may impair interpersonal relationships (Davis et al., 2019), as the lack of physical communication has a negative impact on social interactions (Bolliger & Erichsen, 2013; Tayebinik & Puteh, 2012), and provides less personalized attention from the instructor (compared to traditional learning) (Jacob & Radhai, 2016). Yet for some students, online learning may be the only option for accessing college-level courses (Bettinger et al., 2017).

As noted above, in this study we examine the following Techno-Pedagogical Learning Solutions (TPLS): discussion groups, textual content and digital books, online assignments, surveys/polls, and media.

2.3 Personality and satisfaction with online courses and techno-pedagogical solutions

Learners' personality traits find expression in specific learning behaviors and hence must be considered when designing digital learning (Di Giunta et al., 2013). The Perception of Students Towards Online Learning (POSTOL) instrument developed and validated by Bhagat et al. (2016) focuses on the design and deployment of the features of online courses. For example, the POSTOL considers instructor characteristics by examining how online instructors should conduct themselves, what forms of social interactions are needed, and how the course content should be arranged and sequenced (instructional design). Bhagat et al. (2019) found that students with the personality trait of conscientiousness are more oriented toward systematic course structure and content, which will help them achieve their future learning goals. In addition, research has shown that identifying a learner's personality can help in delivering more effective learning interactions (Tlili et al., 2019a, 2019b) and that personality type may influence student satisfaction with distance learning environments (Bolliger & Erichsen, 2013; Daughenbaugh, Daughenbaugh, et al., 2002; Daughenbaugh, Ensminger, et al., 2002; Soles & Moller, 2001).

Satisfaction is an important factor for measuring online learning effectiveness (Bachari et al., 2012; Kim, 2018). In fact, measuring student satisfaction has become a "hot topic" in higher education research (Cohen & Baruth, 2017; Horzum, 2015; Isik, 2008; Sahinidis & Tsaknis, 2020). Assessments of student satisfaction with online learning environments have typically been quite general. Among other things, they have considered the online platform (Cole et al., 2014), instructor characteristics and online teaching strategies in developing online courses (Almusharraf et al., 2020), and active and collaborative learning (Puška et al., 2021. Many studies found that interactions in the online learning environment are highly correlated with student satisfaction (Dziuban et al., 2015) and that online courses can be tailored to learner satisfaction according to personality type and preferred learning style (Denphaisarn, 2014; Komarraju & Karau, 2005). Indeed, student satisfaction is an important concept that should not be overlooked when evaluating course effectiveness (Bolliger & Erichsen, 2013).

Learners experience online learning differently, depending on their personality type (Santo, 2001). Personality has an impact on learners' satisfaction and achievement (Horzum, 2015; Komarraju & Karau, 2005; Orvis et al., 2011), especially in onkine learning (Bishop-Clark et al., 2007; Bolliger & Erichsen, 2013). As the study of personality and satisfaction with online learning gains momentum (Horzum, 2015; Isik, 2008), it appears that certain personality traits may predict satisfaction and motivation in online courses (Shih et al., 2013). In addition, groups of learners in an online course can be characterized according to their personality and satisfaction (Cohen & Baruth, 2017). In online learning environments, student satisfaction may indicate success, such that satisfied learners appear to be engaged, motivated and responsive (Dziuban et al., 2015). Some have even argued that if students are dissatisfied with their online experience, they may not return for more (Soles & Moller, 2001).

2.3.1 Personality traits and TPLS

Personality affects **online discussions** in several ways and should be taken into account in promoting the potential effectiveness of online communication (Chen & Caropreso, 2004). Extroverts are more active in group discussions than introverts (Lee & Lee, 2006) and more inclined to participate in online discussions (Blau & Barak, 2012). Daughenbaugh, Daughenbaugh, et al. (2002), Daughenbaugh, Ensminger, et al. (2002)) also found that extroverts like the opportunity to be involved in a discussion group. Along with these findings, it is worth noting that extroverts may shy away from online interactions due to the social isolation of this format (as opposed to the physical environment) (Varela et al., 2012). Caspi et al. (2006) found that although neurotic students did not want to post messages they did so. They speculated that the online environment encouraged them to do so to support their learning. Moreover, the asynchronous nature of forums may cause them anxiety if their questions are not answered or posted. These researchers also found that learners with high levels of openness and extraversion were active in online discussions.

An inverse relationship was found between the neuroticism personality type and positive feelings towards navigating **digital books**, while no preference for digital books was found among the other personality dimensions. People with agreeableness type personalities were found to prefer printed books (Bansal, 2011).

Ibrahimoglu et al. (2013) identified groups with similar personalities and related learning styles. They found that students with high levels of extraversion, agreeableness, conscientiousness, and openness preferred to learn by doing and to obtain the correct information by trial and error (such as **assignments**). Note that this particular study did not examine online learning.

Little is known about satisfaction with **media** (videos, and other audio-visual solutions) in the context of the Big Five personality traits. Nevertheless, El Bachari et al. (2012) proposed a learning system that adapts learning technologies to learners' MBTI® personality traits.[1] These researchers claimed that media would be suitable for Sensing and Intuitive types (which may correspond to the openness dimension) and for Thinking and Feeling types (which may correspond to the agreeableness dimension).

No research evidence was found regarding the relationship between **surveys/polls** and personality traits. Note, however, that surveys can facilitate and improve online interaction (Baggaley et al., 2016; Parker & Martin, 2010) and can activate learning, which as mentioned may be more satisfying for some types than for others.

2.4 Personality-based personalized learning paths

As noted, online learning has the potential for customizing learning to learners' needs (Chen & Lin, 2017; Chesser et al., 2020; Soles & Moller, 2001), thus providing a better fit for them (Al-Dujaily et al., 2013; Bourkoukou & El Bachari,

[1] MBTI® personality traits—The Myers-Briggs Personality Type Indicator. A personality model, which classifies human personality into four dimensions consisting of two opposing characters.

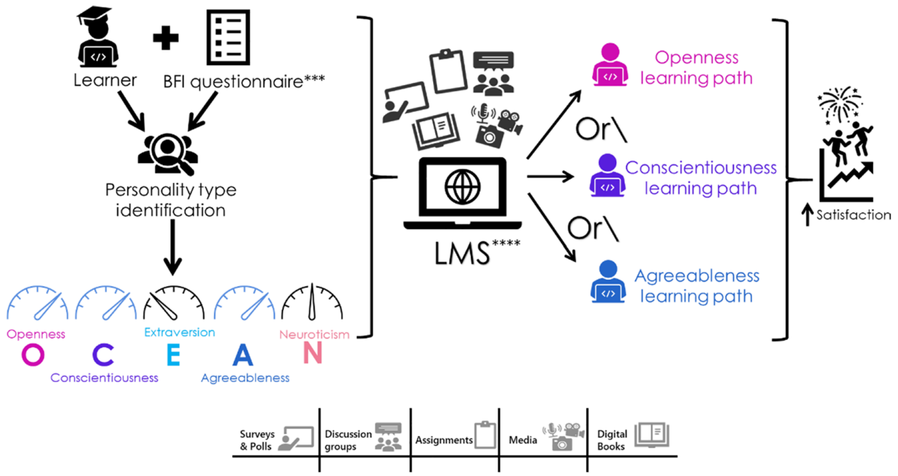

Fig. 1 A model for adapting learning paths to personality types

2016), specifically for university students (Kokkinos et al., 2015). The rising interest in adaptive learning systems has led to the development of adaptive techniques that enable to offer a personalized learning experience (Kim et al., 2013). Therefore, the role of personality traits in education must be examined in the context of the instruction method (Varela et al., 2012).

Personality-based personalization is a growing trend (Lee & Ferwerda, 2017) that may provide more effective learning processes (Ghorbani & Montazer, 2015), while its absence may explain the high dropout rate in online learning (Tlili, et al., 2019a, 2019b).

If personality can affect the level of learner satisfaction while using different learning environments, understanding individual differences may assist in creating and designing learning activities so as to prevent misunderstandings and reduce levels of frustration (Bolliger & Erichsen, 2013). It should be noted that although the concept of personalized learning environments aims to deliver a tailored learning process, learners may also learn with methods that are less satisfying for them (Soles & Moller, 2001), however proper adjustments will be required.

Nevertheless, personalization of the learning environment and customization of the learning process can be problematic, since it is hard to design a fully customized learning program. Moreover, despite the widely recognized benefits of personality-based personalized learning programs, few efforts have been devoted to designing such an adaptive system. This may be due to difficulties in online and automatic personality identification (Chen & Lin, 2017). In order to do so, all differences between learners need to be considered and incorporated into flexible learning environment design (Al-Dujaily et al., 2013). Therefore, this study seeks to offer a model (Fig. 1) that matches learners' personalized learning paths with the TPLS they find satisfying while learning online, in order to increase their satisfaction with the course. According to the model, learner personality types should be determined according to

Big Five trait scores (the dimensions with the highest scores, as defined according to the sample) so they can choose learning paths suited to their personality preferences.

2.5 The research

As indicated in the literature review section, little is known about the relationship between the Big Five personality traits and learner satisfaction with the TPLS available in the online course environment. In this research, we measured students' personality traits and their satisfaction level with the course's TPLS as well as with the course in general. The collected data were used to find correlations and identify groups with similar preferences and needs.

2.6 Research aims and questions

To provide learners a satisfying online learning process, the study sought to find relations between personality traits and satisfaction with the tested TPLS (discussion groups, digital books, online assignments, surveys/polls and media) and to propose a model for raising student satisfaction level using personality-based personalization in an online course. Thus, the research questions explored two aspects:

Q1: What are the relationships between the Big-5 personality traits and satisfaction with the tested course TPLS: media, assignments, discussion groups, textual materials, surveys and polls?
Q2: Can satisfaction with TPLS be used to make a significant classification of groups of online learners with similar personality traits?

3 Methodology

In order to answer the research questions, an anonymous questionnaire was distributed to 108 students who participated in an online learning course at a large accredited university. The tested TPLS were designed especially for this online course and offered to the students during all the course lessons. Students who were diligent in their studies found the learning activities feasible. Each activity was designed for specific learning content. The measured TPLS were integrated so as to facilitate and encourage active and diverse learning. None of the TPLS required prior preparation from the learners, and all of them were designed and planned according to the content being studied. Some of the learning activities were evaluated by the teacher and others were assessed automatically by the learning system.

Participants answered two sub-questionnaires: The first was the version of the BFI (Big Five Inventory) developed by John and Srivastava (1999). It included 44 statements that characterize personality on an ordinal scale ranging from 1 to 5, where 1 indicates "strongly disagree" and 5 indicates "strongly agree." Each trait was examined using various statements: Extraversion ($\alpha = 0.8$); Neuroticism ($\alpha = 0.81$); Agreeableness ($\alpha = 0.68$); Conscientiousness ($\alpha = 0.73$); and Openness to

Experience (α = 0.76) (Etzion & Laski, 1998). An average score for each dimension was calculated according to each participant's scores on the relevant statement. Some statements in the questionnaire were reversed. The second sub-questionnaire was developed especially for the study to measure student satisfaction with each of the course's TPLS and student satisfaction in general. The reliability of the questionnaire was tested (α = 0.78). Students reported their satisfaction on an ordinal scale ranging from 1 to 5, where 1 indicates "not satisfied at all" and 5 indicates "very satisfied". To ensure content validity, two leading researchers in the studied field examined the questionnaire. Their validity confirmation along with the high reliability scores for the sub-questionnaires ensured that the research tools had high validity.

Statistical analyses were conducted on the collected data. Students' personality data in this study were normally distributed based on the degrees of skewness and kurtosis. Spearman's correlation analyses were conducted between personality traits and satisfaction with each of the tested TPLS and with the general satisfaction score. Averages of all five dimensions were calculated to define the "high" types for each dimension (participants with high ratings on a particular dimension). Those with a score higher than the sample average were characterized as "high." Each high dimension was independent and not related to the scores on any of the other dimensions, such that a participant could be rated high on each of the dimensions, or alternatively not rated high on any of the dimensions (if the participant scored lower than the sample average on all the dimensions).

Correlation analysis was performed to answer Q1. In addition, k-means cluster analysis was conducted to characterize groups of learners according to their personality types. After that, a one-way ANOVA analysis was conducted to examine the differences in significance among the group clusters (Q2). Finally, correlation analysis was used to examine the relation between the group clusters and satisfaction with the tested TPLS.

4 Results

4.1 Big Five personality traits and satisfaction levels in online courses—descriptive statistics:

Students' personality characteristics were explored using the Big Five model proposed by Costa and McCrae (1985). Agreeableness emerged as the most dominant trait characterizing the students (Mean = 4.022, SD = 0.575). Conscientiousness also characterized the students with a high score (Mean = 3.950, SD = 0.662). Neuroticism, in contrast, did not have a high score (Mean = 2.704, SD = 0.811) and in fact included the lowest score (MIN = 1.13), while the highest scores were found in both the agreeableness and the conscientiousness dimensions (MAX = 5.00). The widest range of scores and differences within a group were found for the neuroticism trait (SD = 0.811), whereas extraversion exhibited the smallest range of scores (SD = 0.344). The results showed that the students' data in this study were normally distributed based on the degrees of skewness and kurtosis (Table Table 6

Table 1 Descriptive Statistics of each personality trait (**N = 108**)

	Extraversion	Neuroticism	Agreeableness	Conscientiousness	Openness
Mean	3.376	2.704	4.022	3.950	3.732
Median	3.380	2.630	4.000	4.055	3.700
Std. Deviation	0.344	0.811	0.575	0.662	0.621
Skewness	-0.291	0.165	-0.614	-0.560	-0.104
Std. Error of Skewness	0.233	0.233	0.233	0.233	0.233
Kurtosis	-0.236	-0.395	0.650	-0.189	-0.401
Std. Error of Kurtosis	0.461	0.461	0.461	0.461	0.461
Minimum	2.380	1.130	2.110	1.890	2.200
Maximum	4.130	4.630	5.000	5.000	4.900

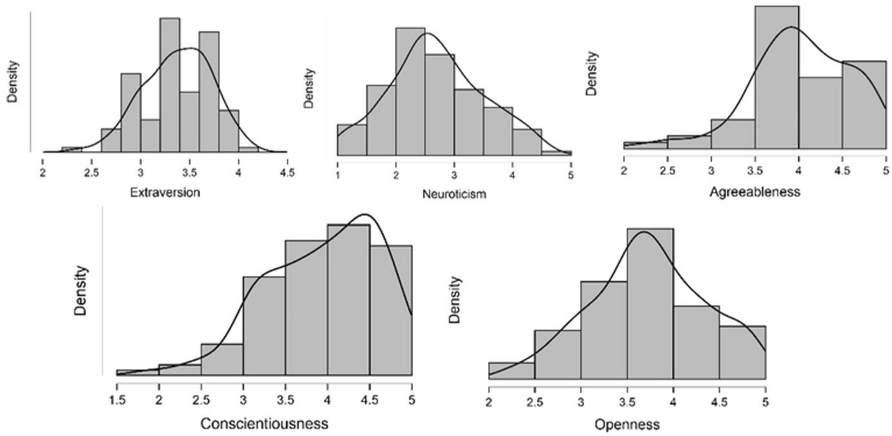

Fig. 2 Personality traits distributions

Satisfaction average scores for each group with each TPLS and in general[Display Image Removed]1).

Figure 2 depicts how the students were distributed according to each personality trait.

Participants were identified as high on a particular dimension if their score was greater than the dimension mean: 58% of all participants were high for extraversion, 47% were high for neuroticism, 45% were high for agreeableness, 56% were high for conscientiousness and 46% were high for openness.

The study's dedicated questionnaire was used to explore student satisfaction with the examined TPLS and with the online course in general. The results indicate that the average general satisfaction level was high (Mean = 4.12, SD = 0.974), while satisfaction with each of the TPLS was moderate-high (Means ranging from 3.389 to 4.157). Scores greater than the mean of all the satisfaction means (Mean = 3.86) were defined as "high" satisfaction for all the satisfaction variables: 78% of the participants reported high satisfaction with media, 73% with assignments, 47% with

Table 2 Descriptive statistics of satisfaction with each TPLS and in general (N = 108)

	Media	Assignments	Discussion groups	Textual materials	Surveys & Polls	General satisfaction
Mean	4.157	4.065	3.389	3.546	3.889	4.120
Median	4.000	4.000	3.000	4.000	4.000	4.000
Std. Deviation	1.015	0.889	1.259	1.122	1.017	0.974
Skewness	-1.142	-0.535	-0.345	-0.279	-0.588	-0.865
Std. Error of Skewness	0.233	0.233	0.233	0.233	0.233	0.233
Kurtosis	0.666	-0.662	-0.782	-0.876	-0.287	-0.287
Std. Error of Kurtosis	0.461	0.461	0.461	0.461	0.461	0.461
Minimum	1.000	2.000	1.000	1.000	1.000	2.000
Maximum	5.000	5.000	5.000	5.000	5.000	5.000

discussion groups, 54% with textual materials, 65% with surveys and polls, and 77% were highly satisfied with the course in general. The results showed that the student satisfaction data in this study were normally distributed based on the degrees of skewness and kurtosis (see Table 2).

4.2 Correlations between personality traits and student satisfaction with TPLS and in general

To answer Q1, we conducted a Spearman analysis to examine the correlation between personality traits and satisfaction level with the five examined TPLS and with the online course in general. As shown in Table 3, many significant correlations were found, with varying degrees of strength. Negative correlations were found between the neuroticism dimension and each of the TPLS, as well as with the online course in general. A high negative link emerged between satisfaction with discussion groups ($r = -0.472$, $p < 0.001$) and general satisfaction ($r = -0.542$, $p < 0.001$). Low-moderate negative correlations were found with all the other TPLS that were tested. A high and significant correlation was found between extraversion and satisfaction with discussion groups ($r = 0.44$, $p < 0.001$), and moderate correlations were found between extraversion and media ($r = 0.217$, $p < 0.001$) and assignments ($r = 0.346$, $p < 0.001$). There were significant high correlations between agreeableness and all satisfaction measures: significant positive correlations were found for general satisfaction ($r = 0.458$, $p < 0.001$), discussion groups ($r = 0.527$, $p < 0.001$) and media ($r = 0.413$, $p < 0.001$). The same strong positive correlation with media was also found for conscientiousness. For those who tend to openness, a strong positive correlation was found with discussion group satisfaction ($r = 0.413$, $p < 0.001$) and a weak moderate correlation with general satisfaction ($r = 0.294$, $p < 0.005$), surveys and polls ($r = 0.231$, $p < 0.05$), and assignments ($r = 0.257$, $p < 0.01$). The correlations strengths are shown in the "heatmap" illustration below (Fig. 3).

Table 3 Correlations between personality traits and all satisfaction measures

Variable		Extraversion	Neuroticism	Agreeable-ness	Conscien-tiousness	Openness
Media	p-value	< .001	< .001	< .001	< .001	—
	Spearman's rho	0.217 *	-0.332 ***	0.413 ***	0.413 ***	0.097
	p-value	0.024	< .001	< .001	< .001	0.319
Assignments	Spearman's rho	0.346 ***	-0.353 ***	0.399 ***	0.339 ***	0.257 **
	p-value	< .001	< .001	< .001	< .001	0.007
Discussion groups	Spearman's rho	0.440 ***	-0.472 ***	0.527 ***	0.249 **	0.413 ***
	p-value	< .001	< .001	< .001	0.009	< .001
Textual mate-rials	Spearman's rho	0.071	-0.235 *	0.254 **	0.325 ***	0.066
	p-value	0.467	0.014	0.008	< .001	0.495
Surveys & Polls	Spearman's rho	0.173	-0.319 ***	0.382 ***	0.323 ***	0.231 *
	p-value	0.073	< .001	< .001	< .001	0.016
General satis-faction	Spearman's rho	0.324 ***	-0.542 ***	0.458 ***	0.335 ***	0.294 **
	p-value	< .001	< .001	< .001	< .001	0.002

4.3 Characterization of student groups according to personality traits

In order to answer the second research question, we attempted to characterize groups of students based on their personality traits using k-means cluster analysis. The variables included the five personality trait scores. The analysis yielded four clusters of similar size and moderate-high quality ($R^2 = 0.509$). The quality of the clusters was affected by the sample size. It should be noted that had the participants been divided into a larger number of groups, the division quality would have increased, but with substantial differences in the sizes of the groups. A one-way ANOVA test was conducted to ensure the significance of the four clusters. Table 4 reveals a significance difference for each trait ($p < 0.001$). An assumptions check was conducted for all five variables and was found to be significant.

Figure 4 and Table 5 show the generated groups according to average score (means) for each personality dimension (high: above 0.5, moderate: from 0.5 to -0.5, low: below -0.5).

Cluster 1 is characterized by participants with significantly high scores on the neuroticism dimension. In fact, in all the other groups, the neuroticism score is low, as is common among the majority of the population in the context of this dimension (Ghorbani & Montazer, 2015). The other dimensions in this group are significantly lower, such that the group can be described by the irregular and dominant measure on the neurotic dimension. In contrast, Cluster 3 represents the opposite situation, with extremely low scores on the neuroticism dimension and high scores on all other

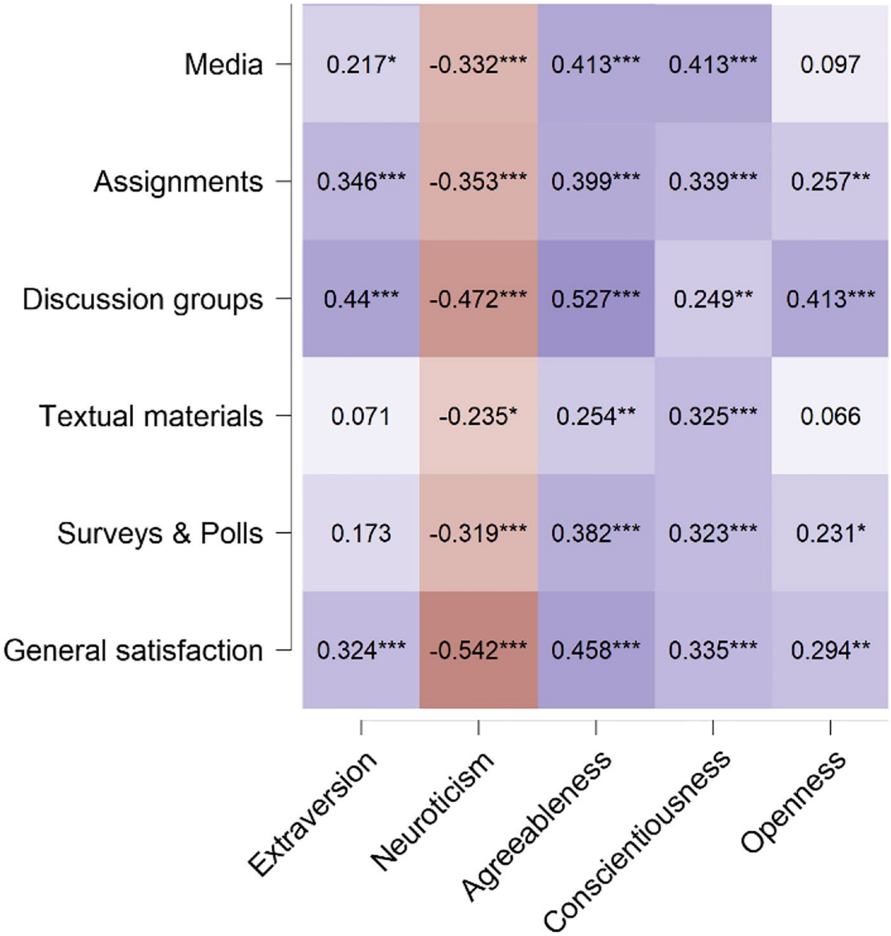

Fig. 3 Spearman's rho "heatmap" for the tested correlations

Table 4 One-way ANOVA test for each trait with the four clusters

	Cases	Sum of Squares	df	Mean Square	F	p
Extraversion	Between groups	6.244	3	2.081	33.607	< .001
	Within groups	6.441	104	0.062		
Neuroticism	Between groups	38.648	3	12.883	42.145	< .001
	Within groups	31.790	104	0.306		
Agreeableness	Between groups	16.477	3	5.492	30.316	< .001
	Within groups	18.841	104	0.181		
Conscientiousness	Between groups	26.276	3	8.759	44.064	< .001
	Within groups	20.673	104	0.199		
Openness	Between groups	19.673	3	6.558	31.557	< .001
	Within groups	21.612	104	0.208		

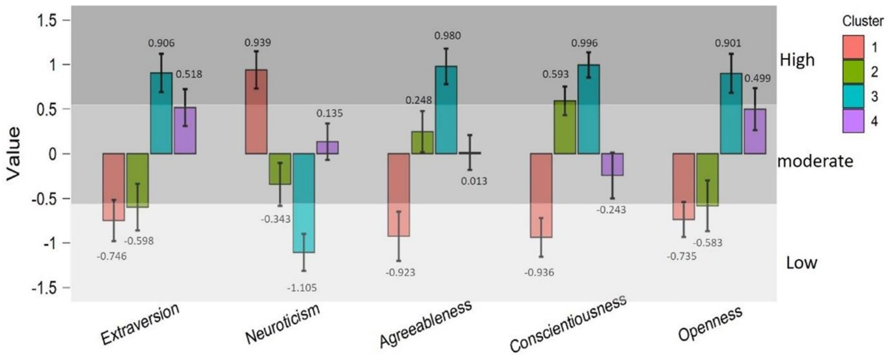

Fig. 4 Graphic illustration of cluster means

Table 5 Personality trait scores in each cluster

No.	Cluster name	Neuro-ticism	Open-ness	Conscien-tiousness	Agreeable-ness	Extraver-sion
1	Neurotic	High	Low	Low	Low	Low
2	Conscientious	Moderate	Low	High	Moderate	Low
3	Non-Neurotic	Low	High	High	High	High
4	Open-Extroverted	Moderate	Moderate	Moderate	Moderate	High

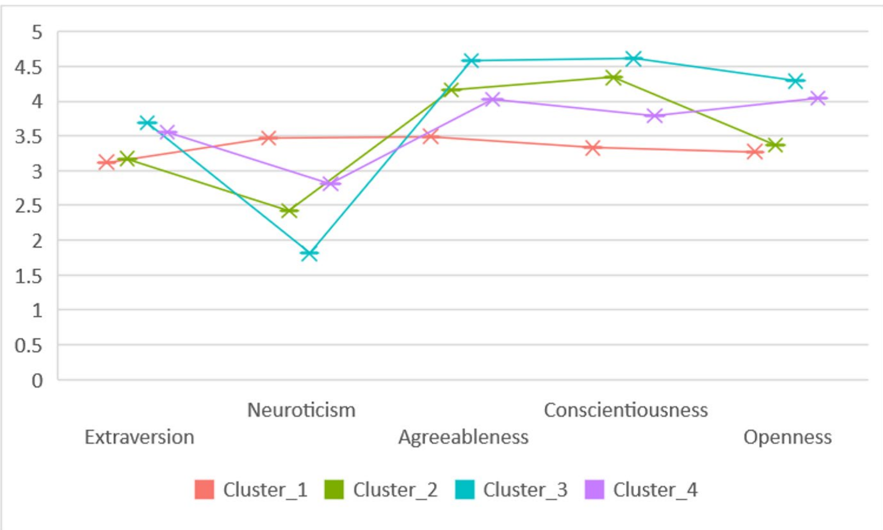

Fig. 5 Comparison of group means scores on each Big Five dimension

dimensions. Hence this group was named the "non-neurotic" cluster. The other two clusters were identified according to the most dominant dimension characterizing them (relative to the group average on all dimensions). Cluster 2 was identified by the conscientiousness dimension and Cluster 4 by the openness and extraversion dimensions. Figure 5 depicts the differences between groups according to mean scores on the Big Five personality dimensions.

4.3.1 Personality clusters and participants' satisfaction with TPLS

To find the most satisfying TPLS for each group of learners, average scores were calculated for each group for each TPLS and in general. As noted, an average score above 3.86 was defined as high satisfaction with all satisfaction variables. In Table 6, the high satisfaction averages for each group are colored in green. The neurotic group (Cluster 1) does not appear to be satisfied with any of the offered TPLS or with the course in general, as opposed to the non-neurotic group (Cluster 2), which had high satisfaction scores on all TPLS. The conscientious group was satisfied with all TPLS except for discussion groups, while the openness/extraversion group (Cluster 4) was satisfied with assignments and media. Apart from the neurotic group (Mean = 3.35), all the groups were highly satisfied with the online course in general.

ANOVA analyses yielded significant differences in TPLS among the four clusters ($p < 0.005$) regarding assignments [$F(3,104) = 12.748$, $p < 0.001$], media [$F(3,104) = 10.385$, $p < 0.001$], discussion groups [$F(3,104) = 9.420$, $p < 0.001$], and surveys and polls [$F(3,104) = 4.659$, $p < 0.005$] (Table 7). Furthermore, significant differences in general satisfaction among the four clusters were found [$F(3,104) = 12.738$, $p < 0.001$]. Notably, no significant differences among the five clusters were found ($p > 0.05$) regarding textual materials.

5 Discussion and Conclusions

The current study examined satisfaction with TPLS among different personality types, with the goal of developing tailored online courses. The findings show that **discussion groups** may be suited to students who tend toward extraversion, agreeableness and openness. These findings are consistent with previous findings about extroverted behavior and preferences (Blau & Barak, 2012; Daughenbaugh, Daughenbaugh, et al., 2002; Daughenbaugh, Ensminger, et al., 2002; Lee & Lee, 2006) as well as openness (Caspi et al., 2006) in discussion groups. With respect to agreeableness, to the best of our knowledge the relationship found in this study has not been observed in previous studies. **Assignments** were found to be satisfying TPLS for extroverted, agreeable and conscientious types, in line with Ibrahimoglu (2013) who found that these types (and the open type as well) prefer to learn by doing. **Surveys** and **polls** were found to be moderately correlated with agreeableness and conscientiousness. Although the literature does not discuss these learning solutions, the findings are in line with the notion that surveys may improve online interaction. Since agreeable types tend to be cooperative (Chesser et al., 2020) and conscientious types are typically prompt, their satisfaction with

Table 6 Satisfaction average scores for each group with each TPLS and in general

No.	Cluster name	Assignments	Media	Discussion groups	Textual materials	Surveys & Polls	General satisfaction
1	The Neurotic	3.42	3.42	2.71	3.29	3.55	3.35
2	The Consciences	4.22	4.48	3.13	3.91	4.17	4.39
3	The Non-Neurotic	4.70	4.65	4.30	3.83	4.39	4.65
4	The Open-Extroverts	4.13	4.29	3.58	3.32	3.65	4.29

polls is reasonable (Bruso et al., 2020). These findings require further examination, as their correlation level is not strong and unambiguous. These two personality types (agreeable and conscientious) were also satisfied with **media**. This particular learning solution has not been examined before in the context of the Big Five, and as far as we know the only empirical evidence for this relation was found in the MBTI® context. El Bachari et al. (2012), assumed that media would be suitable for "sensing-intuitive" and "thinking- feeling" types, which are parallel to the dimensions of openness and agreeableness, respectively (Al-Dujaily et al., 2013; Furnham et al., 2006). Therefore, the present study's findings are partially consistent with previous research. Only the conscientious types reported high satisfaction with **textual materials**. Despite the lack of previous research evidence, their satisfaction may be explained by the notion that digital books help preserve the environment (Bansal, 2011), an essential issue for conscientious learners (Danesh & Mortazavi, 2010).

With respect to the neurotic type, the findings show that those classified as neurotic are dissatisfied with all TPLS (only negative correlations emerged). These findings are consistent with those of previous studies, which found that neuroticism was negatively related to learning satisfaction in face-to-face classrooms as well (Trapmann et al., 2007). The learning dissatisfaction of those classified as neurotic poses a major challenge in attempting to tailor an online course that will satisfy this type of student. Since this personality trait characterizes people who are dissatisfied in general, not only with online learning (Clarke, 2016; Emmons et al., 1985), attempts should be made to reduce their dissatisfaction to some degree rather than trying to satisfy them fully. This can involve helping them believe they are competent of dependable, secure and reliable action within a specified context. Indeed, such confidence was found to predict how students perceive online courses. Neurotic learners tend to be very emotional and have trouble feeling comfortable within a social community (Bhagat et al., 2019). Moreover, previous research (Bansal, 2011) found that neurotic learners prefer printed books. This finding is somewhat surprising, the personal adjustment and search options offered by digital texts (Buzzetto-More et al., 2017) and the possibility of adjusting their learning and reading pace at any time and place should have given them confidence and reduced their anxiety level. Nevertheless, it should be noted that Neuroticism is a complex trait and deserves further investigation. Moreover, from a design perspective, it is not clear what can be done to minimize the negative effects of neuroticism (Bhagat et al., 2019).

In the case of **general satisfaction** with the online course, we found a high correlation with the agreeableness dimension and a moderate correlation with the openness, conscientiousness and extraversion dimensions. These findings are partly consistent with our previous findings, which showed that only openness and conscientiousness significantly predict student satisfaction (Cohen & Baruth, 2017). Open types were also found to be very willing to learn in online environments (Randler et al., 2014). Neurotic types reported significant negative satisfaction levels, which was to be expected as the absence of a teacher makes it difficult for them to connect (Danesh & Mortazavi, 2010).

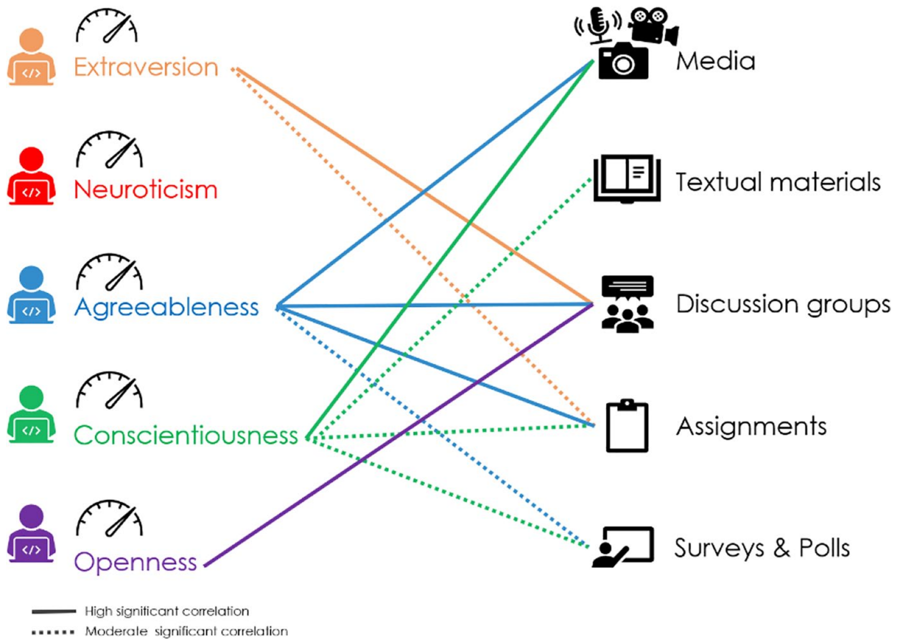

Fig. 6 Optional learning path for each personality type

5.1 Adjusting learning paths according to personality types and their satisfaction with TPLS

As mentioned, the research aim was to offer all personality types appropriate ways to learn online, given the assumption that personality type may influence learners' satisfaction with the learning process (Cohen & Baruth, 2017; Bolliger & Erichsen, 2013; Daughenbaugh, Daughenbaugh, et al., 2002; Daughenbaugh, Ensminger, et al., 2002; Soles & Moller, 2001). According to the findings, learning paths can be designed that will enable learners to choose the TPLS and to adjust the learning to their preferences. This adjustment may increase their satisfaction with the online course. The proposed TPLS found to have a high or medium relationship with the specific personality type can be incorporated into the course, thus enabling learners to choose their learning path. As noted in the literature review, personality comprises a set of dimensions, such that a learner is not characterized according to one type only. Therefore, several solutions may be offered in each learning path, as can be seen in Fig. 6. For example, for learners who score high on extraversion, an online course that includes discussion groups and assignments should be offered. It is important to emphasize that while a particular learning path may also offer other learning methods, solutions that yield high satisfaction will be given priority or offered to a greater extent. As can see in Fig. 6, neurotic types are not satisfied by any of the proposed TPLS, since only negative correlations were found. Hence, students of this type will be able to choose a solution they find less dissatisfying among all the solutions offered (e.g., textual materials (r=-0.235, $p<0.05$), surveys

& polls (r = -0.319, $p < 0.001$) or media (r = -0.332, $p < 0.001$)). Nevertheless, further research is required to examine online course satisfaction among neurotic types.

When adjusting learning paths to learners' satisfaction, it is important to emphasize that the path may also include TPLS that his personality type does not find as satisfying. The number of satisfying learning activities should be higher than those he or she finds dissatisfying. For example, the extroverts' learning path will probably include textual materials, even though they do not find this activity satisfying, but on the other hand, their learning path will also include several discussion group activities.

The cluster analysis in this study yielded remarkably interesting results. First, dividing learners into four groups based on personality dimensions may help in defining learning paths tailored to them. Yet because the Big Five model offers a wide range of personality types (Cohen & Baruth, 2017), it is possible that these four groups do not represent all types of learners. Therefore, further research using a larger sample is required. Examination of the groups indicates an interesting trend: the difficulty neurotics experience in coping with online courses and the offered TPLS. As noted above, creating a satisfying learning path for these learners will be more difficult, thus raising the obvious need to examine learners' preferences and not just their satisfaction level. These preferences will help in developing learning paths offering a variety of preferred learning solutions and not just satisfying solutions.

Clusters 1 and 3 emerged as two inverse groups. In fact, if the sample had been divided into only two clusters, these are the groups that would have emerged, similar to the findings of earlier research (Ibrahimoglu et al., 2013). Our choice of four groups was due to our desire to precisely match learning paths with as many types as possible.

The cluster analysis helped examine satisfaction level with TPLS as reported by the learners. As expected, the neurotic group did not express high satisfaction with any learning solution, although their average satisfaction was moderate for some solutions. Their low satisfaction with the discussion groups is not surprising (Perera, 2016), indicating that it may be advisable to avoid incorporating this solution into learning paths tailored to neurotic individuals. In contrast, the non-neurotic group exhibited high satisfaction with all examined TPLS. This result is consistent with the fact that this group scored highest on all four dimensions, except for neuroticism, on which they scored the lowest compared to all the other groups. This may be the reason for their high satisfaction level with all TPLS.

Those in the conscientious group also expressed high satisfaction with all TPLS, with the exception of discussion groups. A possible explanation for this finding is their relatively low average score on the extraversion dimension (3.170). As mentioned, those with high extraversion tend to be active in discussion groups (Blau & Barak, 2012; Daughenbaugh, Daughenbaugh, et al., 2002; Daughenbaugh, Ensminger, et al., 2002; Lee & Lee, 2006; Nussbaum et al., 2004). Yet this explanation does not apply to Cluster 4, the openness-extraversion group, since their extraversion score was high (3.55) while their average satisfaction with discussion groups was relatively low compared to all other TPLS. A possible explanation is that extroverts may be deterred from online interactions due to their difficulty with social isolation (compared to the physical environment) (Varela et al., 2012). In fact, according to the average satisfaction scores for this group, their adapted learning path should include media and assignments.

We believe that dividing learners into groups with similar personality traits may facilitate the development of online personality-based learning paths. Nevertheless, the results raise questions about the ability of these groups to accommodate a wider range of learners. This issue is likely to be resolved with larger samples in further research. In conclusion, the results of the present study clearly indicate that personality plays a significant role in learners' satisfaction with specific TPLS. Hence, it is necessary to examine whether the correlations found in this study increase learner satisfaction in personality-based personalized online courses. The current study examined a representative group of TPLS. The field of learning technologies offers many additional TPLS solutions that should be examined in the future.

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Data availability Data will be supplied upon request. The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Declaration of interests The authors have no relevant financial or non-financial interests to disclose.

Ethics approval and consent to participate This research received the Institutional Review Board (IRB) approval.

Consent for publication The manuscript does not contain any individual person's data in any form.

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