# Analysis of affective aspects in distance education: a systematic review of the literature from 2015 to 2020

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**ABSTRACT**

**Keywords:** Affective aspects, Distance Education, Systematic Review of Literature.

## 1 INTRODUCTION

Distance Education ("DE"), over the last ten years, has been transforming and, consequently, accentuating the offer of virtual courses in order to allow an education for all Brazilian profiles and contexts (ABED, 2019). The Ministry of Education (MEC) defines Distance Education as:

> [...] educational modality in which students and teachers are separated, physically or temporally, and, therefore, it is necessary to use means of information and communication technologies. This modality is regulated by specific legislation and can be implemented in basic education (youth and adult education, technical high school professional education) and in higher education (MEC, 2020, p. s/n).

The University of Brasília was the pioneer in offering distance education in higher education in 1979. However, other countries had its start earlier, as occurred at the Open University of the United Kingdom with its foundation in 1969 (MOORE e KEARSLEY, 2013).

The DE has as assumption the expansion of access to education by increasing the number of students attended, without the loss of quality in teaching and learning processes (SANTINELLO, 2015). In this scenario, the amount of enrollment grew significantly from 2017 to 2018, totaling more than 1,500,000 new students. The volume was accounted for by the Censo EAD.BR, from 2009 to 2018 (ABED, 2019).

The authors Araújo, Oliveira and Marchisotti (2016) point out some obstacles to student dropout, which can be: problems in reading and interpreting texts, lack of discipline and adversities in handling computers.

In this sense, it is important to understand the profile of these individuals, so that it is possible to analyze the reasons for engagement and dropout in this modality. DE students are characterized by being inserted in the labor market, have commitments related to their family's subsistence, and belong to the age group between 26 and 40 years old. The Censo EAD.BR (2019) concluded that there is a high incidence of students after the typical age of graduation significantly higher at distance than in face-to-face courses.

From this perspective, Behar et al. (2013) clarify that, to become a DE student, it is necessary to build a new identity, that of a virtual student. Thus, one of the primary characteristics emphasized in DE is the learner's autonomy, which requires responsibility in relation to their learning, as well as an ability to manage their demands regarding their training process. Therefore, it requires attitudes and actions consistent with the flexibility that is characteristic of the modality (LOPES e SILVA, 2019). The author Xu (2017) highlights that interventions that promote students' social and academic engagement can help improve their commitment to learning, decreasing the dropout rate. In addition, Figueiredo and Vermelho (2017) point out that the participation of students in the activities and their interaction are critical aspects that depend on planning, study materials, and the appropriate technological structure.

Behar et al. (2013), Ribeiro and Behar (2016) highlight the importance of the student's ability to act with autonomy and expressiveness. The student who does not meet these conditions tends to become unmotivated and discouraged in relation to the studies. The authors also point out that the difficulty of interacting in the virtual space and, consequently, the lack of conviviality with colleagues constitute obstacles to be overcome by the subject who enters this teaching modality.

Thus, it appears that, even in the face of the facilities provided by technology, in favor of interactivity, there are fundamental requirements that must be met by students for a good performance and effective distance learning (BARVINSKI, 2020). Thus, although there is access to an increasing diversity of tools, materials and means of interaction, the way in which these issues affect the educational practices still present challenges to the students..

In DE it is necessary a more active conduct of the actors, whether in their individual or collective construction. Thus, if the needs of DE subjects are not met and conditions and incentives are not found to develop collaboration, engagement, interaction, among others; hardly the student will be able to take control and management of their learning (GODOI and OLIVEIRA, 2016). According to De Almeida and Pillonetto (2019), autonomy, discipline and organization are fundamental qualities for the success of the DE student.

Thus, given the importance of affectivity in energetic mobilization and its intertwining with cognitive development, considering the influence of this aspect in everyday classroom life is relevant in any school context. However, in DE, this element is often neglected. For this reason, it is necessary to implement systems that consider the student's affective state, in order to collaborate with their learning, while helping to prevent dropout, one of the main challenges of this expanding education modality. Thus, the objective of this research was to analyze what types of characteristics the publications considered, how they are inferred, and what the authors understand by social interactions in DE. Regarding the relevance of this investigation, it is noteworthy the identification and discussion about a gap between the affective aspects.

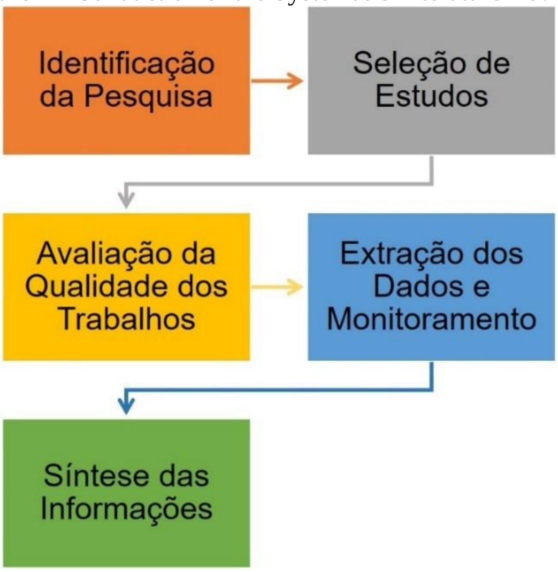
Thus, this article is divided into four sections. In the next section, the research methodology is described, with its development stages. In the third section, the collected results are analyzed and discussed. Finally, the conclusions are presented.

## 2 METHODOLOGY

The Systematic Literature Review (SLR) was conducted in order to identify the considered characteristics, inference, and understanding of the topic of affective aspects in Distance Education. A SLR identifies, evaluates, and interprets all available research relevant to a specific question, topic of interest, or phenomenon of interest by applying a reliable, rigorous, and auditable methodology. The rationale for conducting a review is to identify gaps in current topics in order to suggest areas for future research and to provide a framework for appropriately positioning new research activities (KITCHENHAM, 2007).

In this paper, the conduct of the Systematic Literature Review follows the five steps suggested by Kitchenham (2007), as can be seen in Figure 1.

Figure 1 - Conduction of the Systematic Literature Review.




Source: Elaborated by the authors (2022) based on Kitchenham (2007).

Tradução:
Identificação da pesquisa: survey identification
Seleção de estudos: study selection
Avaliação da qualidade dos trabalhos: work quality assessment
Extração dos dados e monitoramento: data extraction and monitoring
Síntese das informações: summary of the information

Thus, based on Figure 1, the definition of how each step was applied is explained below:

**Survey Identification**: In this step, the search bases were selected. The choice was based on their relevance and the vast amount of titles available regarding affective aspects. Exclusion and inclusion parameters were used for the study. The criteria for rejecting articles were: not having free access; being outside the 5-year period (2015 to 2020); appearing in more than one search base; not contemplating the descriptors used, and not being related to the theme. On the other hand, the criteria for including a paper were: being peer-reviewed and in Spanish, English, or Portuguese. The eight online research sources used were: *Association* *for Computing Machinery* (ACM)[1], Special Committee on Informatics in Education (CEIE)[2], Institute of Electrical and Electronics Engineers (IEEE)[3], *ISI Web of Science* (ISI)[4], Journal Informatics in Education: Theory and Practice (RIETP)[5], Journal New Technologies in Education (RENOTE)[6], *Science Direct* (SD)[7] e *Scopus*[8].

**Study Selection**: In this step the generic *strings* were defined. The keywords applied to the search bases are listed in Chart 1.

Table 1 - *Strings* applied for the search.

| States of Mind or Personality in Distance Education | |
|---|---|
| **Research Bases** | ***Strings* applied to Systematic Literature Review** |
| ACM, IEEE, ISI, SD e *Scopus*. | ((“*moods*” OR “*personality*”) AND (“*distance education*” OR “*e-learning*”)). |
| CEIE, RENOTE e RIETP. | ((“estado de ânimo” OR “personalidade”) AND (“educação a distância” OR “*e-learning*”)). |
| CEIE, RENOTE e RIETP. | “estado de ânimo” OR “personalidade”. |

Source: Prepared by the authors (2022).

The search in these bases gave subsidies for the next step.

**Work Quality Assessment**: To perform this step, exclusion [E] and inclusion [I] criteria were created. To build this theoretical base, five parameters were generated to eliminate and two to add research, as can be seen in Chart 2.

Chart 2 - Exclusion and inclusion criteria.

| Exclusion Criteria | Inclusion Criteria |
|---|---|
| [E1] Articles without free access. | [I1] Peer-reviewed articles. |
| [E2] Studies conducted outside the last five-year period (2015 to 2020). | |
| [E3] Duplicate works. | [I2] Studies in Spanish, English and Portuguese. |
| [E4] Investigations that did not cover the descriptors. | |
| [E5] Research unrelated to the topic. | |

Source: Prepared by the author(s) (2022).

In this context, the first [E1] exclusion criterion indicates the impossibility of free access to the full original text. The second [S2] contemplates more recent studies on the areas, providing a current and contextualized discussion. The third [R3] concerns articles presented in more than one database. The fourth [R4] delimits that the research should mention relations to the theme. Finally, for the analysis of the last criterion [E5], the abstract was read and a diagonal reading was performed, considering the introduction,

[1] Disponível em: http://portal.acm.org
[2] Disponível em: http://www.br-ie.org/pub
[3] Disponível em: https://ieeexplore.ieee.org/Xplore/home.jsp
[4] Disponível em: http://www.isiknowledge.com
[5] Disponível em: http://seer.ufrgs.br/InfEducTeoriaPratica
[6] Disponível em: https://seer.ufrgs.br/renote
[7] Disponível em: http://www.sciencedirect.com
[8] Disponível em: https://www.scopus.com/home.uri

the main topics, and the final considerations, trying to identify if they present a relationship with the theme. For the inclusion criteria, [I1] points to articles that were peer-reviewed to ensure the quality of the work and [I2] refers to studies in Spanish, English and Portuguese, so that it was possible to read them without the need for translation resources.

**Data Extraction and Monitoring**: In this paper, the Research Questions (RQ) that were sought to be answered by analyzing all the papers were defined. Thus, a total of three RQW were elaborated, as illustrated in Chart 3.

Chart 3 - Research Questions about affective aspects in DE.

| **Moods or Personality in Distance Education** |
|---|
| RQ1) What characteristics are considered in studies about affective aspects in DE? |
| RQ2) How are personality or emotion inferred in Distance Education? |
| RQ3) What do the authors understand by affective aspects in DE? |

Source: Prepared by the authors (2022).

The Research Questions enabled the development of the next step.

**Summary of the Information**: In this step, the data obtained from the RQ elaborated were summarized. As a support for the construction of this theoretical base, the Parsifal tool was used, which allows one to follow and register the process of inclusion and exclusion of articles.

Thus, based on these steps, in the next section the results are presented.

## 3 RESULTS

In this subsection are described works that are related to the theme of affective aspects in the context of Distance Education (DE). In the articles, it was sought to analyze what types of characteristics the studies consider, how they are inferred and what the authors understand by affectivity. Thus, an investigation was carried out in international databases (ACM, IEEE, ISI, SD and Scopus) using the following descriptor: ((“*moods*” OR “*personality*”) AND (“*distance education*” OR “*e-learning*”)). On the other hand, in the national repositories (CEIE, RENOTE e RIETP) *string* was applied: ((“estado de ânimo” OR “personalidade”) AND (“educação a distância” OR “e-learning”)). It is worth mentioning that the RIETP database did not provide any studies with the descriptors and *strings* previously applied, so we changed it to “estado de ânimo” OR “personalidade” and applied it to the Portuguese surveys, so that it could broaden the possibilities in order to obtain results, even if less specific.

Thus, after the searches, a total of 3,470 publications were obtained in the eight databases. Thus, the five exclusion criteria were applied. The first [S1] indicated the impossibility of free access to the original full text. The second [E2] corresponded to papers that were not recent in the area, i.e., outside the period from 2015 to 2020. The third criterion [E3] concerned the articles that were presented in the searches in both databases. For the fourth [E4] it was delimited that the searches should contemplate the descriptors used. Finally, for the analysis of the last [S5], the articles that were not related to the theme were excluded. Therefore, from the initial total of publications found, each exclusion criterion was applied sequentially, as shown in Table 1.

Table 1 - Exclusion criteria applied to the databases.

| Database | General Search | Exclusion Criteria | | | | |
|---|---|---|---|---|---|---|
| | No filters by Type or Period | E1 | E2 | E3 | E4 | E5 |
| ACM | 387 | 387 | 203 | 202 | 9 | 4 |
| CEIE | 38 | 38 | 25 | 22 | 18 | 8 |
| IEEE | 115 | 2 | 0 | 0 | 0 | 0 |
| ISI | 242 | 36 | 25 | 16 | 2 | 1 |
| RENOTE | 2 | 2 | 1 | 1 | 1 | 1 |
| RIETP | 5 | 5 | 2 | 2 | 1 | 0 |
| SD | 2.166 | 483 | 232 | 229 | 13 | 1 |
| *Scopus* | 515 | 36 | 23 | 22 | 5 | 3 |
| **Total** | **3.470** | **989** | **511** | **494** | **49** | **18** |

Source: Prepared by the authors (2022).

In this way, Chart 4 shows the 18 papers found, as well as their respective abstracts.

Chart 4 - Related work on affective aspects in Distance Education.

| STUDIES ON AFFECTIVE ASPECTS IN DISTANCE EDUCATION | | |
|---|---|---|
| **Year** | **Author(s)** | **Abstract** |
| 2015 | Antonio A. A. Machado et al. (2015). Personalitatem lexicon: Um léxico em português brasileiro para mineração de traços de personalidade em textos. **Brazilian Symposium on Computers in Education**, v. 26, n. 1, p. 1122-1126. Available at: http://dx.doi.org/10.5753/cbie.sbie.2015.1122. | The paper presented initial studies on the correlation of lexical information in Brazilian Portuguese texts with psychological features of the Big Five model and the NEO-IPIP facets. As results it is intended to build or adapt a lexicon that incorporates sentiment and possible personality traits. |
| 2015 | Fabrícia Damando Santos et al. (2015). Análise de evidências do estado de ânimo desanimado de alunos de um AVEA: uma proposta a partir da aplicação de regras de associação. **Workshops do Congresso Brasileiro de Informática na Educação**, v. 4, n. 1, p. 1054-1063. Available at: http://dx.doi.org/10.5753/cbie.wcbie.2015.1054 | The research aimed to highlight the student's discouragement when performing individual or group activities in a Virtual Teaching and Learning Environment. As results, it was possible to verify that discouraged students submitted less than 50% of the activities and had difficulties with the content, reflecting in the final concept. |
| 2016 | Ana Raquel Faria et al. (2016). Building an Emotional Adaptive Platform. **Proceedings of the Ninth International C* Conference on Computer Science & Software Engineering**, p. 1-6. Available at: https://dl.acm.org/doi/abs/10.1145/2948992.2948994. | The research described how to build a prototype of an Emotional Adaptive Platform, which is used to perceive the student's emotional state, personality and learning preference and adjust the course based on these points. As results, the data collected from the tests performed showed that there is a statistical difference between student learning by analyzing two platforms, one that takes emotional state into account and the other that does not. There is an indication that by introducing the component to the platform, student learning can be improved. |
| 2016 | Guanliang Chen et al. (2016). On the impact of personality in massive open on-line learning. **Proceedings of the 2016 conference on user modeling adaptation and personalization**, p. 121-130. Available at: https://dl.acm.org/doi/abs/10.1145/2930238.2930240. | The research explored the extent to which students' personalities impact their learning and behavior in a massive open online course (MOOC). The results indicate that conscientiousness is positively correlated with three Forum characteristics: the number of replies, posts, and interactions. Students with a high degree of extroversion spend less time on the Forum compared to those with a low level. It was also found that the correlation coefficients tend to increase as the weeks of the course progress, as more activity data on each |

| | | |
|---|---|---|
| | | student is collected, and extroversion and neuroticism achieve greater predictive accuracy by the end of the course. |
| 2017 | Ina Blau, Orli Weiser e Yoram Eshet-Alkalai (2017). How do medium naturalness and personality traits shape academic achievement and perceived learning? An experimental study of face-to-face and synchronous e-learning. **Research in Learning Technology**, v. 25, p.1-23. Available at: https://eric.ed.gov/?id=EJ1163190. | The paper examined how academic performance and the cognitive, emotional and social aspects of perceived learning are affected by the level of average naturalness (face-to-face learning *versus* synchronous *e-learning* through videoconferencing) and by the personality traits (neuroticism, emotional stability, extroversion and introversion) of the students. As results, it was found that videoconferencing present in the medium naturalness, intensified the cognitive aspect of perceived learning, but compromised the emotional and social ones. Regarding personality traits, neurotic students tend to enjoy and succeed more in face-to-face learning, while those with emotional stability succeed in both learning conditions (face-to-face and e-learning). Extroverts prefer face-to-face environments, although they perform less well in these conditions. Finally, introverts performed better in face-to-face learning. |
| 2017 | Sintija Petrovicaa, Alla Anohina-Naumecaa e Hazım Kemal Ekenelb (2017). Emotion recognition in affective tutoring systems: Collection of ground-truth data. **Procedia Computer Science**, v. 104, p. 437-444. Available at https://doi.org/10.1016/j.procs.2017.01.157. | The paper analyzed sixteen existing emotion recognition methods most commonly employed in Intelligent Tutor Systems with the goal of choosing one, in this case *Self-Assessment Manikin* (SAM). As a result, a self-assessment mechanism was implemented for the three emotional dimensions of SAM; pleasure, arousal, and dominance. |
| 2017 | Taís Borges Ferreira e Marcia Aparecida Fernandes (2017). Detecção de traços de personalidade em textos para apoiar a formação de grupos para colaboração. **Brazilian Symposium on Computers in Education,** v. 28, n.1, p. 1627-1636. Available at: http://dx.doi.org/10.5753/cbie.sbie.2017.1627. | The goal was to provide a means of detecting personality traits and making this information available to support grouping strategies for collaboration. The results found suggest that matching students alters the degree to which a particular personality trait influences the group, such as conscientiousness. |
| 2018 | Abir Abyaa, Mohammed Khalidi Idrissi e Samir Bennani (2018). Predicting the learner's personality from educational data using supervised learning. **Proceedings of the 12th International Conference on Intelligent Systems: Theories and Applications**, p. 1-7. Available at: https://dl.acm.org/doi/abs/10.1145/3289402.3289519. | The paper identified the dimensions of student personality based on the *Big Five* and used educational data resources to develop an automatic classifier that predicts personality based on its traits in an online learning system. The results revealed that most of the five dimensions; openness to experience, affability, extroversion, and neuroticism, can indeed be anticipated using educational resources. Conscientiousness did not, necessitating the need to collect more data and select other means. |
| 2018 | Devon Allcoat e Adrian Von Mühlenen (2018). Learning in virtual reality: Effects on performance, emotion and engagement. **Research in Learning Technology**, v. 26, p.1-13. Available at: https://doi.org/10.25304/rlt.v26.2140. | The research was intended to compare three learning conditions: traditional (textbook style), virtual reality, and video (passive control). Each individual took a knowledge test before and after the use of the learning situations. The results point out that participants in the traditional and virtual reality conditions improve overall performance compared to those in the video circumstance. The subjects who used virtual reality also remember more of the content than the other two categories. Self-evaluation showed an increase in positive emotions and decrease in negative emotions for virtual reality, while in the traditional and video conditions the reverse occurred. Finally, students reported greater engagement when using virtual reality. |
| 2018 | Mahdi Rahmani Hanzaki e Carrie Demmans Epp (2018). The effect of personality and course attributes on academic performance in MOOCs. **European conference on technology enhanced learning**. Springer, Cham, p. 497-509. Available at https://doi.org/10.1007/978-3-319-98572-5_38. | The paper analyzed personality and collaboration level to predict academic performance in a massive open online course (MOOC). The result revealed that increasing the level of collaboration can significantly amplify performance. |
| 2018 | Nabia Siddiquei e Ruhi Khalid (2018). The relationship between personality traits, learning styles and academic performance of e-learners. **Open Praxis**, v. 10, n. 3, p. 249-263. | The study established links between personality traits, learning styles, and academic performance of students enrolled in *e-learning* courses. The personality traits considered were openness to experience, affability, conscientiousness, extroversion, and |

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|---|---|---|
| | Available at: https://www.learntechlib.org/p/187321/. | neuroticism. The learning styles were divided into: active, global, intuitive, reflective, sequential, sensitive, verbal, and visual. Finally, academic performance (GPA) was classified into: high achievement, motivated learning, and effective learning. The results point out that extroversion was positively related to all learning styles, while neuroticism was negatively linked. It was also revealed that GPA was positively correlated with openness to experience, affability, and conscientiousness, and negatively with neuroticism. Similarly, academic performance was positively correlated for active, global, and intuitive learning styles. Negative for reflective, sequential, and sensitive. However, no relationship was found between verbal and visual styles. |
| 2018 | Taís Borges Ferreira et al. (2018). Detecção automática de traços de personalidade e recomendação de agrupamento com o modelo *Big Five*. **Brazilian Symposium on Computers in Education,** v. 29, p. 1643-1652. Available at: http://dx.doi.org/10.5753/cbie.sbie.2018.1643. | The present research aimed to form groups that are good for collaboration, being considered those in which all members work on solving a task and communicate in a way that makes social interaction possible. As a result, the groups in which individuals demonstrated greater participation and high interaction, most had high conscientiousness in the personality trait. |
| 2019 | Carla Adriana Barvinski et al. (2019). Refinamento dos fatores motivacionais e estados de ânimo a partir do uso de Mineração de Dados Educacionais. **Revista Novas Tecnologias na Educação**, v. 17, n. 3, p. 214-223. Available at: https://www.seer.ufrgs.br/renote/article/view/99472. | The objective was to present an Educational Data Mining approach to identify behavior patterns related to motivational factors and mood states in student interactions in a Virtual Learning Environment. As a result, it was found that student's (dis)motivation is directly related to their state of mind, and can suffer both positive and negative changes according to the degree expressed in the motivational factors of Confidence, Effort, and Independence. |
| 2019 | Cleon Pereira Junior et al. (2019). Personalização das interações de um agente conversacional utilizando emoções e perfis de personalidade. **Brazilian Symposium on Computers in Education,** v. 30, n. 1, p. 1092-1100. Available at: http://dx.doi.org/10.5753/cbie.sbie.2019.1092. | The research aimed to develop an affective Conversational Agent based on the Theory of Personality Profiles and emotions for personalized student support in the learning process. The results suggest that the student with the astute profile remained cheerful at all times and that of the total number of students (n=19) who performed the task, 73.68% used the Conversational Agent as a support. Thus, the use of the Agent demonstrated a positive form regarding the learner's state during the execution of activities in a VLE and a motivation in the learning context. |
| 2019 | Felipe Morais e Patricia Jaques (2019). Predição de emoções baseada em Mineração de Dados: considerando a personalidade para melhorar a detecção. **Brazilian Symposium on Computers in Education,** v. 30, n. 1, p. 1521-1530. Available at: http://dx.doi.org/10.5753/cbie.sbie.2019.1521. | The goal was to verify whether the students' personality data can provide an improvement in the accuracy of emotion detection in learning. As a result, it was possible to identify that only engagement obtained a small improvement in detection accuracy. |
| 2019 | Hend Alabdullatif e Ángel Velázquez Iturbide (2019). Personality traits and the intention to continue to use the Smart Learning Technologies: The role played by internal and external motivations in the relationship between the Big Five Personality Traits and the Intention to Continue to Use MOOCs (ICM). **Proceedings of the Seventh International Conference on Technological Ecosystems for Enhancing Multiculturality**, p. 663-670. Available at: https://dl.acm.org/doi/abs/10.1145/3362789.3362886. | The aim was to examine the role of three personality traits; affability, conscientiousness and extroversion in understanding variations in levels of intention to continue using a massive open online course (MOOC) considering external and internal motivations. The results show that none of the traits had a significant direct impact, internal motivation for affability and conscientiousness is important for understanding the relationship between personality and intention to continue in MOOC. Extroversion is externally motivated, but there was no evidence to support a mediating impact. |
| 2019 | Rachel Reis e Seiji Isotani (2019). Formação de Grupos em Ambientes CSCL baseada na combinação entre os Traços de Personalidade e Teorias de Aprendizagem Colaborativa. **Anais dos Workshops do Congresso Brasileiro de Informática na Educação,** v. 8, n. 1, p. 1001-1010. Available at: | The paper verified the influence of personality traits on group formation based on learning theory. As results, a Formal Model for generating learning roles was created and an algorithm was developed that used these roles to support more effective group formation. |

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| | http://dx.doi.org/10.5753/cbie.wcbie.2019.1001 | |
| 2019 | Rodrigo Smiderle, Sandro Rigo e Patricia Jaques (2019). Estudando o impacto da gamificação na aprendizagem e engajamento de alunos de acordo com os traços de personalidade e a orientação motivacional. **Brazilian Symposium on Computers in Education,** v. 30, n. 1, p. 793-802. Available at: http://dx.doi.org/10.5753/cbie.sbie.2019.793. | The paper analyzed the effect of gamification on students' behavior and engagement according to their personality traits and motivation. The experimental evaluation was performed on half of the students using the gamified version and the other half not. The results showed that the group that had a significant improvement in the quality of solutions submitted was the gamified one. The students who had intrinsic motivation obtained a higher number of points, medals, and accuracy in both groups. In addition, in both groups there was an improvement in accuracy with low personality levels of friendliness and openness to change. |

Source: Prepared by the authors (2022).

The results of the research (Chart 4) provide an overview of the investigations that are being carried out in relation to affective aspects in DE. The two publications in 2015 are national, while the two in 2016 are international. In 2017, three studies were found, two in English and one in Portuguese. Then, in 2018, there are five articles, four international and one national, and in 2019, five studies were developed in Portuguese and one in English. Thus, it is possible to realize that the researches deal with national (nine) and international (nine) scopes and that the area has been gaining prominence in investigations, because in the years 2018 and 2019 there was an increase in publications that total 11 of the 18 papers analyzed.

Therefore, it was possible to observe that the articles apply different techniques to analyze personality and emotion. In the research of Machado et al. (2015), Data Mining was applied to subjectivity in texts, in the *Personalitatem Lexicon*, to identify the personality traits of an individual. Santos et al. (2015) used Educational Data Mining to analyze patterns of disheartened student behavior in a Virtual Teaching and Learning Environment. The publication by Chen et al. (2016) employed regression using *Spearman*'s correlation coefficient to measure the effectiveness of each of the personality traits. Faria et al. (2016) adopted Descriptive Statistics to compare the results of the groups that used the emotional adaptive platform with those that did not. The work of Blau, Weiser, Eshet-Alkalai (2017) applied mean and standard deviation to the variables personality traits, mean naturalness, and perceived learning. Authors Ferreira and Fernandes (2017) used linear regression algorithms, radial basis function, Gaussian process, decision trees, and multilayer perception network to classify student personality traits in a VLE.

The paper by Petrovicaa, Anohina-Naumecaa, and Ekenelb (2017) adopted the *AffectButton* tool that allows users to give emotional *feedback* about their feelings, moods, and attitudes in an Intelligent Tutor System Abyaa, Idrissi, and Bennani (2018) analyzed seven different supervised learning classification algorithms, these being *Support Vector Machines*, *k-Nearest Neighbors*, *Naïve Bayes*, *Random Forest*, J48, Logistic Regression and *Bagging*, using personality scores for each dimension (high or low) as values. Allcoat and Mühlenen (2018), meanwhile, conducted a knowledge test before and after the application of traditional media, virtual reality, and video to verify the learning experience and emotions. Ferreira et al.'s (2018) study employed statistics to identify students' personality traits in forming groups in a Virtual Learning Environment. Hanzaki and Epp's (2018) research adopted Machine Learning algorithms for two different sets of courses: one using personality and the other integrating the former with collaboration level as predictors of academic performance. Siddiquei and Khalid's (2018) research analyzed Pearson's correlation coefficient to assess the relationship between personality traits, learning styles, and academic performance of students enrolled in *e-learning* courses.

Alabdullatif and Iturbide (2019) used correlational analysis to explore the relationships between personality traits and intention to continue in MOOC, and structural equation modeling using Partial Least Squares Methods to investigate the learning path. The publication by Barvinski et al. (2019) employed Educational Data Mining to examine patterns of behavior related to motivational factors and learners' mood in a VLE. The work of Junior et al. (2019) applied emotion detection to *Application Programming Interface*, developed by Microsoft, which captures student typed text. For the overall evaluation of the conversation between the Conversational Agent and the student, the Logistic Regression technique is used, which allows the prediction of values by a categorical variable. The paper by Morais and Jaques (2019) adopted Data Mining on learner interactions in an Intelligent Tutor System to detect four emotions: confusion, engagement, frustration, and boredom. Reis and Isotani (2019) applied *Pearson*'s correlation coefficient to calculate the interdependence between personality traits and learning, motivation, and satisfaction variables. The study by Smiderle, Rigo, and Jaques (2019) investigated the data of students' actions in *Feeper*, which is a web environment to support learning programming by doing, recorded during the experiment to analyze the effect of gamification.

Table 5 discusses the methods applied in each publication found, as can be seen below.

Chart 5 - Methods applied to affective aspects in Distance Education.

| Study | Method |
|---|---|
| Machado et al. (2015), Santos et al. (2015), Ferreira and Fernandes (2017), Abyaa, Idrissi and Bennani (2018), Hanzaki and Epp (2018), Barvinski et al. (2019) and Morais and Jaques (2019). | Educational Data Mining. |
| Chen et al. (2016), Faria et al. (2016), Blau, Weiser, Eshet-Alkalai (2017), Ferreira et al. (2018), Siddiquei and Khalid (2018), Alabdullatif and Iturbide (2019) and Reis and Isotani (2019). | Statistics. |
| Petrovicaa, Anohina-Naumecaa and Ekenelb (2017), Junior et al. (2019) and Rigo and Jaques (2019). | *Plugins*. |
| Allcoat and Mühlenen (2018). | Questionnaires. |

Source: Prepared by the authors (2022).

In this scenario, it was possible to verify, based on Table 5, that seven researches (MACHADO et al., 2015; SANTOS et al., 2015; FERREIRA and FERNANDES, 2017; ABYAA, IDRISSI and BENNANI, 2018; HANZAKI and EPP, 2018; BARVINSKI et al., 2019; MORAIS AND JAQUES, 2019) apply the Educational Data Mining (EDM) technique to analyze affective aspects in DE.

Affective aspects are inferred in different ways. The research of Machado et al. (2015) draws on the *Big Five* model (GOLDBERG, 1992) and the NEO-IPIP facets (NUNES, 2008) to analyze a set of words written by students in the interactions of a Chat. The investigation by Santos et al. (2015) used students' behavioral data obtained from communications performed in Moodle to identify their affective states. Faria et al. (2016) analyze two questionnaires, the *Big Five* (COSTA and MCCRAE, 1992; GOLDBERG, 1990) and the VARK (FLEMING and BAUME, 2006). The publication by Blau, Weiser, Eshet-Alkalai (2017) applied two questionnaires: the NEO-PIR by Blau and Barak (2012) to measure personality traits and the self-report to gauge perceived learning that assesses three subscales: cognitive, emotional, and social aspects (CASPI and BLAU, 2008; 2011).

The papers by Chen et al. (2016), Ferreira and Fernandes (2017), Ferreira et al. (2018), Abyaa, Idrissi, and Bennani (2018), and Hanzaki and Epp (2018) employ the *Big Five* model (DE RAAD, 2000). The article by Petrovicaa, Anohina-Naumecaa, and Ekenelb (2017) used the *Self-Assessment Manikin* to measure the three emotional dimensions (RUSSELL and MEHRABIAN, 1977). Allcoat and Mühlenen (2018) asked participants to complete two questionnaires: in the first, participants were to rate their emotions at surprised, amazed, and stunned on values from 1 (not at all) to 5 (very strongly). In the second, the scale for measuring web-based learning tools was used to measure engagement (KAY, 2011). The study by Siddiquei and Khalid (2018) applied Goldberg's *Big Five* (1993).

Alabdullatif and Iturbide (2019) employ DeYoung et al.'s (2016) Big Five Personality Traits (BFPT). Barvinski et al.'s (2019) research used the IFP (PASQUALI, AZEVEDO, and GHESTI, 1997), which is a psychological test based on personality traits. Junior et al.'s (2019) research applied the Personality Profile Theory of Cloninger et al. (1993) and Chatbot (2005). Morais and Jaques' (2019) publication analyzed the logs generated by students' interaction with an Intelligent Tutor System to detect and predict learning emotions. Reis and Isotani's (2019) paper used the EPQ-J personality test (EYSENCK, 2013). The paper by Smiderle, Rigo, and Jaques (2019) applied the IGFP-5 to assess personality dimensions (DE ANDRADE, 2008).

In this context, it was observed that the affective aspects are inferred mainly through the *Big Five* questionnaire, in which five researches apply the test developed by De Raad (2000) and other three investigations employ the one created by Goldberg (1990; 1992; 1993) and Costa and Mccrae (1992), as presented in Chart 6.

Chart 6 - Inference of affective aspects by the authors.

| Study | Questionnaire | Author(s) |
|---|---|---|
| Machado et al. (2015), Faria et al. (2016) and Siddiquei and Khalid (2018). | *Big Five.* | Goldberg (1990; 1992; 1993), Costa and Mccrae (1992). |
| Chen et al. (2016), Ferreira and Fernandes (2017), Ferreira et al. (2018), Abyaa, Idrissi and Bennani (2018) and Hanzaki and Epp (2018). | *Big Five.* | De Raad (2000). |
| Machado et al. (2015). | NEO-IPIP. | Nunes (2008). |
| Faria et al. (2016). | VARK. | Fleming and Baume (2006). |
| Blau, Weiser, Eshet-Alkalai (2017). | NEO-PIR e Autorrelato. | Blau and Barak (2012) and Caspi and Blau (2008; 2011). |
| Petrovicaa, Anohina-Naumecaa and Ekenelb (2017). | *Self-Assessment Manikin.* | Russell and Mehrabian (1977). |
| Alabdullatif and Iturbide (2019). | BFPT. | DeYoung et al. (2016). |
| Barvinski et al. (2019). | IFP. | Pasquali, Azevedo and Ghesti (1997). |
| Reis and Isotani (2019). | EPQ-J. | Eysenck (2013). |
| Smiderle, Rigo and Jaques (2019). | IGFP-5. | De Andrade (2008). |

Source: Prepared by the authors (2022).

Thus, analyzing the publications, it was possible to verify that, with the exception of the works by Santos et al. (2015) and Morais and Jaques (2019) that respectively use the data of the interactions performed in Moodle and the logs, all the others require the student to fill out at least one questionnaire in order to be able to detect their personality or emotion. As limitations of these articles, students who do not want to answer the test are eliminated from the sample, since there is no way to examine their affective aspects.

The understanding of affective aspects in EaD is understood in different ways, the research of Machado et al. (2015) analyzes the personality of Goldberg (1992) that formalizes it through five major traits defined in the *Big Five* model: openness, extroversion, neuroticism, achievement and socialization. It also considers Nunes' NEO-IPIP (2008) which is a secondary model to identify the facets of each major personality trait, these being: fantasy, aesthetics, feelings, actions, ideas, values, anxiety, anger, depression, embarrassment, impulsivity, impulsiveness, vulnerability, welcoming, gregariousness, assertiveness, activity, sensation seeking, positive emotions, competence, order, sense of duty, striving for achievement, self-discipline, thoughtfulness, confidence, frankness, altruism, complacency, modesty, and sensitivity.

Santos et al. (2015) consider mood states, which are: Satisfied, Excited, Discouraged and Dissatisfied, because they are affective phenomena that have a longer duration of time and can be inferred in VLE (LONGHI, 2011). Whereas, Faria et al. (2016) perceive through the *Big Five* model, composed of the elements: openness, extroversion, neuroticism, achievement and socialization (COSTA and MCCRAE, 1992 and GOLDBERG, 1990) and the VARK covering four dimensions: visual, aural, reading/writing and kinetic, to determine learning preferences (FLEMING and BAUME, 2006). The publication by Blau, Weiser, Eshet-Alkalai (2017) was based on Costa and McCrae's (1992) model of the five major personality traits that consider: openness, extroversion, neuroticism, achievement, and socialization.

The work of Chen et al. (2016), Ferreira and Fernandes (2017), Ferreira et al. (2018), Abyaa, Idrissi, and Bennani (2018), and Hanzaki and Epp (2018) applied the *Big Five* model encompassing five dimensions: openness to experience, affability, conscientiousness, extroversion, and neuroticism (DE RAAD, 2000). The article by Petrovicaa, Anohina-Naumecaa, and Ekenelb (2017) interpreted the fundamental emotional dimensions, considered pleasure, arousal, and dominance. Pleasure indicates how pleasant the person feels about something, arousal describes the level of mobilization or energy expended, and dominance symbolizes the ability to cope with the situation (RUSSELL e MEHRABIAN, 1977).

Allcoat and Mühlenen (2018) use an adapted version of Izard et al.'s (1974) differential emotions scale, with nine categories of emotions: interest, amusement, sadness, anger, fear, anxiety, contempt, surprise, and exaltation. The study by Siddiquei and Khalid (2018) understands by affective aspects Goldberg's Big Five model (1993), which considers openness to experience, affability, conscientiousness, extroversion, and neuroticism. Alabdullatif and Iturbide (2019), on the other hand, employ the *Big Five* personality traits (BFPT) which are openness to experience, friendliness, conscientiousness, extroversion, and neuroticism, according to DeYoung et al. (2016).

Barvinski et al.'s (2019) research looked at moods such as Satisfied, Excited, Discouraged, and Dissatisfied (LONGHI, 2011), and motivational factors such as Confidence, Effort, and Independence (BERCHT, 2001). The research by Junior et al. (2019) considered the primary emotions; joy, sadness, anger, fear, disgust, and surprise (CHATBOT, 2005) and the Personality Profile Theory of Cloninger et al. (1993) and Chatbot (2005), which is composed of three psychological dimensions, novelty seeking, avoidance of punishment and pain, and the need for reward. Each of these are assigned levels, resulting in nine personality profiles, defined by: reckless, theatrical, excessive, cunning, meticulous, affective, docile, hermit, and flexible.

Reis and Isotani's (2019) publication characterized Eysenck's (2013) personality traits: mental rigidity, conscientiousness, extroversion, amiability, and emotionality. Smiderle, Rigo, and Jaques (2019) use the IGFP-5 which addresses the five personality factors, being openness, conscientiousness, extroversion, amiability, and neuroticism (DE ANADRADE, 2008). Finally, the work of Morais and Jaques (2019) analyzed the emotions based on Calvo and D'Mello (2010) which are confusion, frustration, boredom, and engagement.

Table 7 presents the summary of how the authors of the articles defined the affective aspect, seen below.

Chart 7 - Authors' understanding of affective aspect.

| Estudo | Affective Aspect |
|---|---|
| Machado et al. (2015), Faria et al. (2016) and Blau, Weiser, Eshet-Alkalai (2017). | Personality defined as: openness, neuroticism, extroversion, socialization, and achievement. |
| Machado et al. (2015). | Facets of each personality trait are: fantasy, aesthetics, feelings, actions, ideas, values, anxiety, anger, depression, embarrassment, impulsiveness, vulnerability, welcoming, gregariousness, assertiveness, activity, sensation-seeking, positive emotions, competence, order, sense of duty, striving for achievement, self-discipline, thoughtfulness, confidence, frankness, altruism, complacency, modesty, and sensitivity. |
| Santos et al. (2015) e Barvinski et al. (2019). | States of mind, which are: Satisfied, Excited, Discouraged, and Dissatisfied. |
| Chen et al. (2016), Ferreira and Fernandes (2017), Ferreira et al. (2018), Abyaa, Idrissi and Bennani (2018), Hanzaki and Epp (2018) and Siddiquei and Khalid (2018). | Personality conceptualized as: openness to experience, affability, conscientiousness, extroversion, and neuroticism. |
| Petrovicaa, Anohina-Naumecaa and Ekenelb (2017). | Emotional dimensions: pleasure, excitement and dominance. |
| Allcoat and Mühlenen (2018). | Nine categories of emotions: interest, amusement, sadness, anger, fear, anxiety, contempt, surprise, and exaltation. |
| Alabdullatif and Iturbide (2019) and Smiderle, Rigo and Jaques (2019). | Personality traits that are: openness to experience, friendliness, conscientiousness, extroversion, and neuroticism. |
| Junior et al. (2019). | Primary emotions: joy, sadness, anger, fear, disgust, and surprise.<br><br>Personality profiles: reckless, theatrical, excessive, cunning, meticulous, affectionate, docile, hermit, and flexible. |
| Reis and Isotani (2019). | Personality traits: mental rigidity, conscientiousness, extroversion, amiability, and emotionality. |
| Morais and Jaques (2019). | Emotions: confusion, frustration, boredom, and engagement. |

Source: Prepared by the author (2022).

Thus, based on the analysis of Chart 7 it was possible to see that twelve studies consider personality as an affective aspect, while only two publications investigate moods.

In this way, the next section presents the conclusions.

## 4 CONCLUSION

Brazilian education presents a growth in the offer of virtual courses, obtaining an increase in the number of students in the Distance Education modality (DE). The physical distance that occurs between the actors in this modality makes their relationships unique. Thus, given the particularities of DE, it is important to consider the relevance that affective aspects play in the teaching and learning processes. From this perspective, the present study analyzed what types of characteristics the publications consider, how they are inferred, and what the authors understand by affective aspects in DE.

In this context, for the investigated theme, 18 studies were found in the eight search bases. Thus, from the results presented in this article, it was possible to see that the characteristics of the affective aspects are through the *Big Five* questionnaire. The inference in seven works was applied from the technique of Educational Data Mining and the authors in five investigations consider the personality as: openness to experience, affability, conscientiousness, extroversion and neuroticism.

Regarding the limits of this research, it is noteworthy that it was conducted in the period from 2015 to 2020, that is, before the pandemic of COVID-19, so it is possible that new research considering the affective aspects have been published. However, this work sought to analyze the panorama before the pandemic, because the intention was to verify in DE and post-pandemic, other modalities suggest.

Therefore, there is an indication that, although the theme has been growing in the last two years in quantity of works, totaling eleven, the articles that consider the excitement, discouragement, satisfaction and dissatisfaction have a vast field of investigations to be explored. It is worth mentioning that a constant monitoring of the students' affectivity in DE allows the teacher to personalize teaching by meeting the individual needs of each subject, and may influence the dropout factor.

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