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Cluster analysis for tailored tutoring system
Uso della cluster analysis per la creazione di un sistema di tutoraggio personalizzato e basato sui dati [1]

di

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Abstract
In online courses, the tutoring activities are relevant for the learners' training; they affect the course quality and imply creating dynamic and active online learning environments.

[1] The contribution represents the result of a joint work of the authors that collaborated in all the phases of the research work. Tommaso Minerva, scientific responsible for the planning of the research project, provided the general setting of the paper; Annamaria De Santis wrote the sections 4 and 5 (with the subsections); Katia Sannicandro the sections 2 and 3; Claudia Bellini the sections 1 and 6.

The research aims to define a model based on a structured and data-driven tutoring system to identify homogeneous groups of students attending a blended degree course and, then, set tailored interventions as support.
We chose a multivariate data analysis technique, cluster analysis, and used personal data and academic achievements of first-year students (*n*=110) in Degree Course in Digital Education at the University of Modena and Reggio Emilia to create groups of similar learners, identify common characteristics of students in each group and define personalized tutoring strategies for each cluster.
The analysis allows identifying six homogeneous clusters of students and defining activities to design that concern the fields of content, motivation and metacognition, involve degree course tutors and teachers, and be carried out individually or in small groups of students.

Keywords: Tutoring Activities; Educational Data Analysis; Cluster Analysis; Blended Courses

Abstract
Nei corsi online, la presenza di tutor (disciplinari, tecnici, metodologici) è rilevante per la formazione degli studenti; le attività di tutorato influenzano la qualità delle azioni didattiche e contribuiscono a creare ambienti di apprendimento online dinamici e attivi.
La ricerca qui presentata mira a definire un modello per la creazione di sistemi di tutoraggio *data-driven*, strutturato e personalizzato, che rilevi gruppi omogenei di studenti in un corso di laurea erogato in modalità prevalentemente a distanza per i quali attuare specifici interventi di supporto.
Abbiamo scelto una tecnica di analisi multivariata dei dati, la cluster analysis, e raccolto, selezionato e utilizzato i dati personali e i dati relativi ai risultati accademici degli studenti del primo anno del Corso di Laurea in Digital Education dell'Università di Modena e Reggio Emilia (*n*=110) per creare gruppi di studenti simili, identificare le caratteristiche comuni degli studenti in ogni gruppo e definire strategie di tutoraggio personalizzate per ogni cluster.
L'analisi ha permesso di individuare sei cluster omogenei di studenti e di definire alcune azioni di tutoraggio personalizzate per ciascun gruppo a partire dai risultati conseguiti negli esami del primo anno. Le attività da progettare e proporre riguardano l'approfondimento dei contenuti, la motivazione e la metacognizione, coinvolgono tutor e docenti e possono svolgersi individualmente o in piccoli gruppi.

Parole chiave: Tutoring Activities; Educational Data Analysis; Cluster Analysis; Blended Courses

1. Introduction

The beginning of a new degree course (as every training path) is the right moment to shape how teaching, student relations, and extracurricular activities have to be designed and managed. In a blended course, the use of online teaching environments and tools in addition to the traditional ones brings other questions: what digital resources and tools can be included in the online learning environment? Who supports the teachers in designing the course? How to alternate between synchronous and asynchronous activities? What forms of confrontation among teachers, learners, and other involved professionals?

In the blended degree course in Digital Education at the University of Modena and Reggio Emilia, launched in the a.y. 2019/20, the answers to the above questions on the course delivery methods were centred on the benefits that students can acquire from participating in the course, with attention to instructional design processes, online environment hosting the courses, students' professional development (De Santis et al., 2021), both technical and methodological support. At the end of the first year of the course, we had at our disposal the results of the exam grades of first-year students, valuable data to taking stock of the students' progress and course success. We questioned whether these data could provide us with indications on possible interventions to support the students in order to improve their educational experience and enhance their professional development.

This reflection gave rise to the research we are proposing.

Starting from selecting variables relating to academic success and using a multivariate analysis technique, we have tried to hypothesize a set of procedures for constructing a tailored and data-driven tutoring system to be re-proposed in other training contexts.

This system does not focus only on technical support activities, is not carried out only by specific figures but involves the entire team working on the degree course in activities that complete the students' university experience.

The paper starts with a discussion of tutoring methods and actions in online or blended courses (sections 2 and 3) and proposes a description of the analysis method used on the sample composed of students in the Digital Education course (sections 4, 5, and 6).

2. Distance learning and tutoring

Numerous studies and researches support the growth of blended education and online courses in the university context. They connect the position of tutor with instructional design and e-Learning and, in recent years, to the broader framework of distance education with a focus on student engagement process (Price et al., 2007; Chen et al., 2010; Henrie et al., 2015; Li et al., 2017).

In online courses, the tutor role and activities are relevant for the learners' training; they affect the course quality and imply creating dynamic and active online learning environments (MacDonald, 2008; Kizilcec & Schneider, 2015; Tait, 2003; Paul & Tait, 2019).

Instructional design and training course management, in general, need these "support" figures, both in university than in other training contexts, face-to-face as online.

Despite this, the importance of the tutor's role, as Helen Lentell said (2004), is often underestimated and limited in the complex framework of distance education. His work of student's support is often linked just with administrative and less "academic" aspects; support instead must involve the management and "animation" of the didactic environment based on personalisation, individualisation, and collaboration within the learning process. These dynamics have to be linked to the possibility for students to enjoy their own times and spaces in the learning management, to follow courses on formal and informal environments (e.g.,

MOOCs) designed for their learning needs, and to develop a sense of community also linked to the inclusive role of technologies (Rivoltella, 2017).
Also in Italian scenario, the “classic” role of tutor is grown with a new development of his competencies and responsibilities, asked from the other professional figures involved in training processes (teachers, instructional designers etc.) (Rotta & Ranieri, 2005; Ferrari et al., 2021; Ferrari & Triacca, 2020; Vegliante & Sannicandro, 2020).
What’s changed? What’s guided the research in the last years? The research has moved attention on predictive model “that exploit recent systems of learning analytics (LA) with the ability to act in “real time” and with direct repercussions on the “process” of designing the courses” (Sannicandro et al., 2019, p. 30).
Still considering the support activity, also Intelligent Tutoring Systems use the large amount of data collected in online platforms to automatically support user experience (Damasceno et al., 2020). As evidenced by Akkila and colleagues (2019) in the Intelligent Tutoring System (ITS), there are four basic components involves (Sottilare et al., 2013):

1. the knowledge model
2. the student model
3. the pedagogical model
4. the user interface model

Figure 1 shows the pedagogical model in which the comparison from teacher and tutor on learning course design, content choice, mode of use, assessment, and management of interactive didactic (virtual classroom, collaborative activities etc.) is fundamental. It is a paradigmatic change – slow but stable – that involves all figures, including teachers asked to reconsider and re-design their own teaching activity.

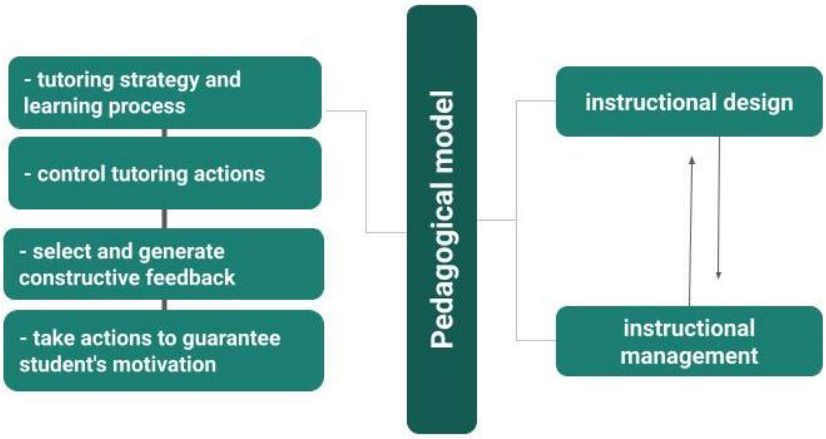

Figure 1 - *Pedagogical model* (reworked from Akkila et al., 2019).

3. Tutoring skills and psychological needs

In the complex development of the learning context where professionals work (university, higher education, online environment), there is a need for an interdisciplinary team and a competence analysis.

In 2003 the Commonwealth of Learning[2] (O'Rourke, 2003) analyse four areas connected to tutor's competencies and their relation: supportive, administrative, instructional and facilitative. Moreover, particular attention deserves "academic skills into two significant skill domains: guiding and enabling" (p. 39, Table 1).

GUIDING LEARNING	ENABLING LEARNING
• using content knowledge to provide direction • providing feedback to learners on their work • familiarising learners with the conventions of the discipline • academic problem solving • linking	• helping learners to develop their skills in organising concepts, in developing "mental maps" that enable them to structure their learning in a way that makes sense to them • helping learners to articulate their ideas in writing or verbally, and to debate them productively • fostering learners' ability to achieve learning goals through interactions such as cooperative projects or peer feedback • setting appropriate and challenging topics for learner discussions, helping learners to focus on the topic and providing a framework that develops their skills in managing discussions • modelling effective learning strategies for learners by demonstrating alternative

Table 1 - *Academic skills into two significant skill domains: guiding and enabling – Commonwealth of Learning* (O'Rourke, 2003, p.47, 49).

Guiding and enabling learning are used particularly for collaborative activities in digital learning environments, favouring social and metacognitive activities (Kopp et al., 2012).

A recent systematic review of Massuga and collegues (2021) focused on the tutor's skills to develop and critical points, for example, connected to the change of teaching model or the use of synchronous systems for student interaction. Authors, in accordance with Li and colleagues (2017), identify 7 roles:

1. Instructor
2. Instructional designer
3. Learning facilitator/advisor
4. Technologist
5. Social
6. Evaluator
7. Manager/Administrator

[2] "The Commonwealth of Learning (COL) is the world's intergovernmental organisation solely concerned with the promotion and development of distance education and open learning" (https://thecommonwealth.org/).

200 groups of competencies and 98 tasks are added to roles. What roles and competencies have a major priority? First, the largest number of skills are inside of role as Instructor, Evaluator and Instructional designer (Li et al., 2017) and regards:

- "Facilitate the cognitive processing of course content
- Evaluate the course
- Develop course content
- Facilitate course interaction
- Motivate the students" (p. 200).

In 2017 studies, the participation of tutors in the design and development of courses was still not evident; after four years, the framework has changed. The tutor is present from the first design stage of a course and not just as marginal support. It can provide, for example, course construction guidelines to faculty, monitor all phases of course development, verify alignment between learning objectives and training content and so on.

In line with Goold and colleagues (2014), it is important also to pay attention of student's expectations, connected to *Self-determination theory*[3] – SDT (Deci & Ryan, 2012) that regard three areas: autonomy, competence, relatedness. Self-determination theory "centers on how particular motives are integrated and regulated by individuals, to achieve more adaptive behavior. As individuals remain in continuous contact with their environment, SDT focuses on how ideas, values and goals are internalized according to the influence of several variables in the social context" (Fandiño & Velandia, 2020, p. 2). In fact, learning processes are related to learners' specific characteristics and also to the motivation to learn influenced by tutoring actions.

In the blended context it seems necessary a new design of times and modality of (synchronous and asynchronous) lessons. The emergence of COVID-19 has highlighted some critical issues, but at the same time has strengthened the methods and opportunities for online interaction and confrontation among teachers, learners, and tutors. It became clear that the design and management of synchronous and asynchronous activities must necessarily be an integral part of blended teaching; these activities are often neglected and focused on the "transmission of content" and not on "comparison" between teachers, learners, and other involved figures. They are often relegated to alternative moments than traditional teaching.

Respect to this complex scenario, the research questions that directed the study are:

- What tutoring and support activities can be offered in university courses for students with similar profiles based on academic success data?
- What tutoring actions can foster social and meta-cognitive activities in the academic digital learning environment?
- What data collection and analysis procedures can be proposed to define a model for creating a tutoring system that can be reproduced in other academic contexts?

[3] "Self-determination theory (SDT) is an empirically derived theory of human motivation and personality in social contexts that differentiates motivation in terms of being autonomous and controlled" (Deci, Ryan, 2012, p. 416).

4. Methods

Starting from the above research questions, in this paper, we try to delineate and use a model for defining tailored tutoring activities in three actions:

1. to identify variables describing students' characteristics and distinguishing similar types of students;
2. to choose a data analysis technique to create similar groups among students;
3. to describe students' profiles for each group and define some tutoring activities to propose to each group of students according to the different profiles.

We used data collected among first-year students in the Degree Course in Digital Education at the University of Modena and Reggio Emilia for testing the three phases and define some features of a potential tutoring system suitable for this course and for students in the sample.

4.1 Data and Variables

The research sample is composed of 110 students enrolled in the Degree Course in Digital Education. During the analysis, we excluded observations with missing data in some variables and those corresponding to students who decided not to enrol to the second course year. The sample was thus reduced to 86 observations.

We collected data for each student through a brief online questionnaire (Q) and information registered in the university database (A). The variables we examined are of two types:

- *Personal Data* (Q/A), in particular the variables: gender, age, previous degree, working status, high school type and grade. The questionnaire was mainly useful for collecting information on the previous degree and working status that are not detailed and updated in university information systems.
- *Academic Achievements* during the first course year (A), that is: the grade of each of 7 exams in the first year, the weighted average of exams grades (AVE_EXAMS), the percentage of university credits acquired (P_ECTS), the percentage of exams passed in the semester when the course was (P_SEM_EXAMS), the percentage of failures (n. failures/n. attempts, FAIL_VALUE).

The dataset is available at https://rb.gy/uunqmc.

4.2 Cluster Analysis

Many factors intervene in the determination of each phenomenon observed in educational research. In the case described here, the definition of the profile of a university student has to take into account simultaneously several elements (personal data, work activities, academic results) which constitute a complex descriptive framework. This is why a multivariate technique was needed to determine the relationships between the variables and the grouping. The use of multivariate analysis responds to the need to handle several variables in a single context and synthesise them to obtain information on broad and multifaceted scenarios (Bartholomew et al., 2008).

In the definition of a model for a tailored and data-driven tutoring system in this research, we used cluster analysis, which is a multivariate analysis technique used to create homogeneous groups among observations starting from a set of quantitative and qualitative variables varying simultaneously. In this descriptive multivariate data analysis technique, the researcher assumes the existence of a natural structure where clusters of observations are grouped starting from their multivariate profile (Hair et al., 2014). Therefore, we have chosen cluster analysis over other dependence techniques where group membership is determined only by one variable that is indicated a priori (as, for example, the dependent variable in logistic regression). Cluster analysis is used in many contexts in educational research for grouping and distinguishing observations in a sample to differentiate characteristics of students or training events (some examples: Kovanović et al., 2019; Schmidt et al., 2018; Perna & Leigh, 2017).

Our analysis aimed to create similar clusters of students starting from their own features. The variables used for clustering are the summary variables about Academic Achievements. Those related to Personal Data were to describe the clusters obtained by the analysis.

We calculated similarity with the Manhattan distance method and employed the complete-linkage method as a hierarchical agglomerative clustering algorithm.

Analysis was conducted using the statistical software R and, in particular, ggdendro, ggplot2, psych packages.

The choice of a set of variables and a multivariate analysis technique is the starting point to define a model to be used in different degree courses to design support activities for first-year students.

5 Results and discussions

5.1 Preliminary analysis

In the sample, 73 % were women; students' ages ranged from 20 to 56 years, half of them were older than 26 years. 63% were working when the questionnaire was administered, 15% had a previous degree. These data, differing from a typical university course, may be due to the delivery course mode (blended).

The weighted mean of exams grade was between 24 and 27/30 for half of the students; the same number of students passed more than 75% of their exams, had a failure rate of less than 25%, and completed 50% of their exams in the right semester.

In the Personal Data group, we found a correlation (ρ) between PRE_DEGREE and AGE (0.33), WORKING (0.26), HS_GRADE (0.20), and between AGE and WORKING (0.51). As guessed, it is more common for adult learners to work and have already obtained a qualification.

In the Academic Achievement group, ρ is -0.58 between FAIL_VALUE and P_ECTS and -0.23 between FAIL_VALUE and AVE_EXAMS. There isn't a linear correlation between the average of exam grades, the percentage of failures, and the percentage of exams passed in the proper semester. The number of failures (withdrawal from the examination or flunking) is negatively correlated with the number of examinations passed and the average of grades obtained. A student with high grades and a high number of exams passed has got lower failures.

Considering the linear relations between the two variables groups, we saw some correlations among which the one between AVE_EXAMS and AGE (0.29), PRE_DEGREE (0.39). This means that the average of exam grades increase with age and the completion of previous degree courses.

5.2 Cluster analysis

We explored solutions from 3 to 8 clusters. The six-cluster solution was selected as the more appropriate. The dendrogram in Figure 2 shows the hierarchical clustering procedure in place. In Figure 3 the boxplots represent the distribution of clusters according to the variables on Academic Achievements.

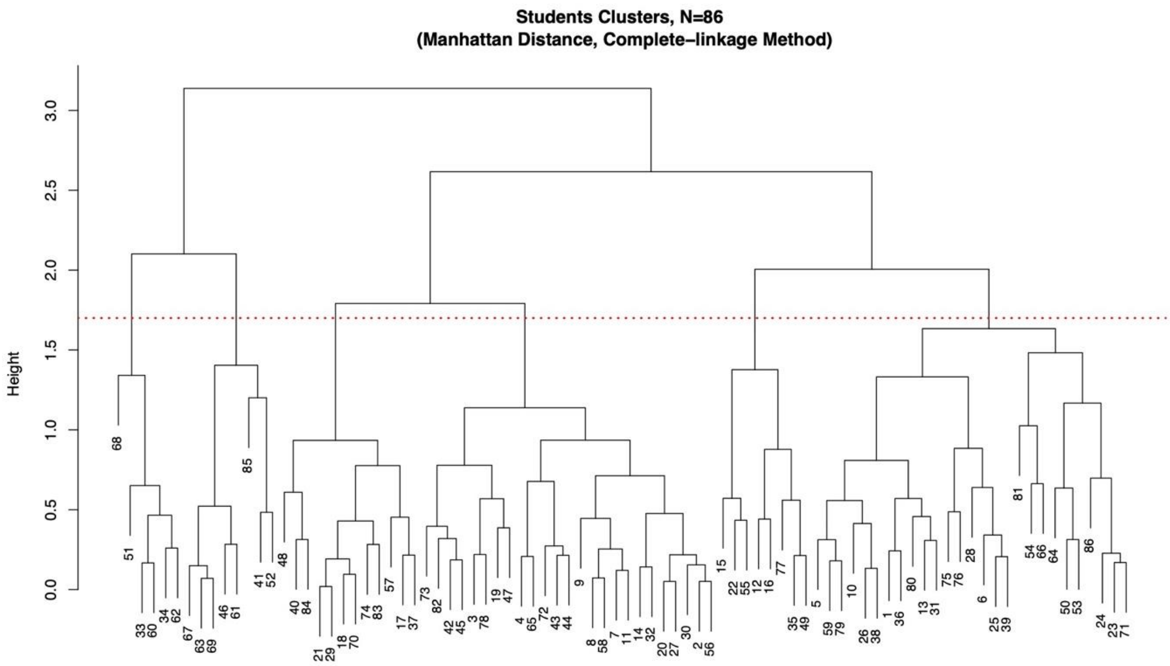

Figure 2. *Dendrogram of clustering, cut for the six-cluster solution (red line).*

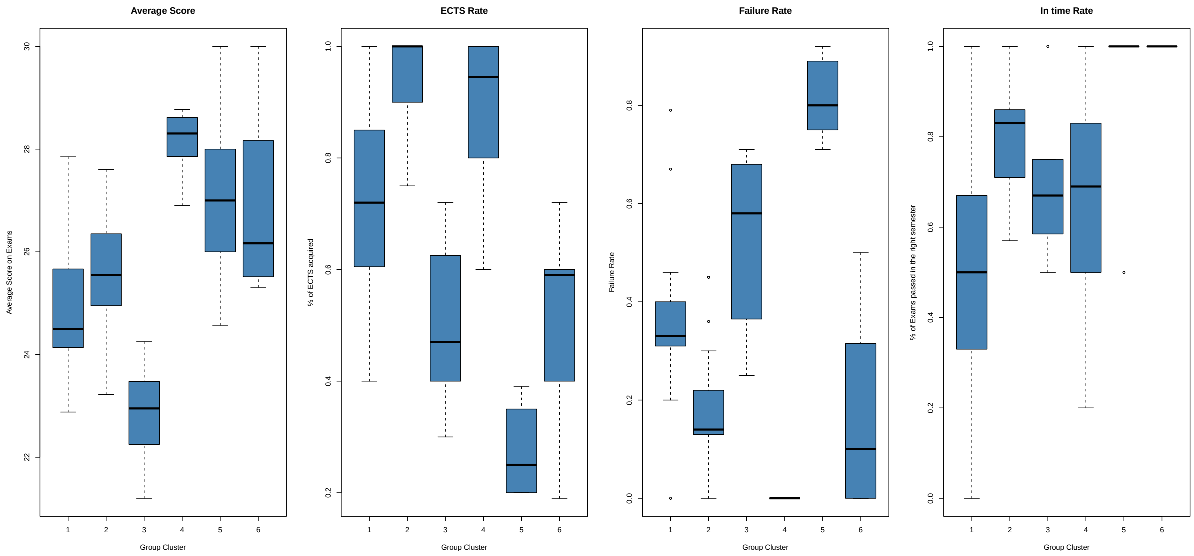

Figure 3. *Boxplot of Academic Achievement variables for the 6 clusters*.

We provide a description of the clusters according to the study variables and propose some support activities to be implemented for each of them.

The students (*n*=27) belonging to the CLUSTER 1 obtained positive results in their academic careers. Data show that they are involved and active in training. Tutoring activities in small groups held by degree course tutors can strengthen their motivation and abilities in managing study times. Also, content tutoring for specific disciplines with teachers and content experts can reinforce their knowledge.

The students (*n*=25) in CLUSTER 2 are able to organize their time in a successful way: they passed exams following the university schedule. They could enhance their performance by deepening their knowledge in each discipline and acquiring new strategies for implementing their study method.

The students (*n*=8) in CLUSTER 3 showed difficulties in learning and time managing. They passed a few exams in the right semester with poor results, and their failure rate is high. This shows that they are not able to stay on track. One-to-one tutoring about both content and study methods is needed.

Performance levels by the students (*n*=12) of CLUSTER 4 (that are adults and workers) are very high. In this case, tutoring activities do not aim to overcome learning difficulties but to provide students with resources and solutions through which they can create networks with their course colleagues and use the acquired skills in social and work contexts to the best of their potential.

The students who belong to CLUSTER 5 (*n*=6) have passed a low number of exams with good grades but cannot keep up with university activities. The failure rate is high. They need content tutoring to catch up on missed exams and one-to-one meetings with tutors to organize their activities and acquire skills in managing study time.

Results for CLUSTER 6 (*n*=8) are very similar to those of cluster 5 but differ for low values of failure rate. Here again, we proposed one-to-one tutoring aimed at understanding the level of motivation and engagement in university activities (also questioned by the fact that the number of both passed exams and attempts to pass exams is low).

The analysis suggested interventions referring to three types of support: support for content learning, support to manage study organisation (metacognition), support to enhance motivation. We did not exclude reinforcement actions for clusters where students showed particularly positive results.

6. Conclusions

The data collection and analysis techniques used in the research allow identifying homogeneous groups of students and defining some tutoring actions starting from their academic results. The activities to design for each cluster concern the fields of content, motivation and metacognition, involve degree course tutors and teachers, and be carried out individually or in small groups of students.

The tutoring system suggested by the data analysis is not only linked to a tutor's support activities for daily practical difficulties but goes further. It takes care of students' needs and prompts us to think of teaching activities that teachers can implement, of extra-curricular activities on topics such as motivation or metacognition (Kopp et al., 2012; Van Leeuwen et al., 2015) that can be of interest to everyone, of one-to-one support activities that can be conducted by a tutor who takes on new roles and skills.

These actions and the preliminary theoretical reflection in the opening of the contribution represent a first step towards constructing a structured and data-driven tutoring system that could be used in the newly established degree course in Digital Education and, in future, in other blended degree courses in our university.

The model building procedure, that at the moment is suitable also for traditional courses, could be revised by introducing other variables in the analysis, in particular those that have to do with participation in blended courses such as activity completion, connection time, number and type of logs.

As further work, we could refine the choice of the number of clusters on the basis of fitness functions under study and carry out a comparison with Self-organising Neural Networks.

References:

Akkila, A.N., Almasri, A., Ahmed, A., Al-Masri, N., Sultan, Y.A., Mahmoud, A.Y., & Abu-Naser, S.S. (2019). Survey of Intelligent Tutoring Systems up to the end of 2017. *International Journal of Academic Information Systems Research* (IJAISR), *3*(4).

Bartholomew, D.J., Steele, F., Moustaki, I., & Galbraith, J.I. (2008). *Analysis of multivariate social science data* (2nd ed.). Boca Raton (FL): CRC press, Taylor & Francis Group.

Chen, P.S.D., Lambert, A.D., & Guidry, K.R. (2010). Engaging online learners: The impact of Web-based learning technology on college student engagement. *Computers & Education*, *54*(4), 1222-1232.

Damasceno, A.R., Martins, A.R., Chagas, M.L., Barros, E.M., Maia, P.H.M., & Oliveira, F.C. (2020, October). STUART: an intelligent tutoring system for increasing scalability of distance education courses. In *Proceedings of the 19th Brazilian Symposium on Human Factors in Computing Systems* (pp. 1-10).

Deci, E.L., & Ryan, R.M. (2012). Self-determination theory. In P.A.M. Van Lange, A.W. Kruglanski, & E.T. Higgins (Eds.), *Handbook of theories of social psychology* (pp. 416-436). Sage Publications Ltd.

De Santis, A., Sannicandro, K., Bellini, C., & Minerva, T. (2021). The training of Digital Education professionals. *Lifelong Lifewide Learning*, *17*(38), 324-338.

Fandiño, F.G.E., & Velandia, A.J.S. (2020). How an online tutor motivates E-learning English. *Heliyon*, *6*(8).

Ferrari, S., Mauro, I., Messina, S., Raviolo, P., & Rivoltella, P.C. (2021). E-tutoring nella didattica telematica. Pratiche di modellamento. *Excellence and Innovation in Learning and Teaching-Open Access*.

Ferrari, S., & Triacca, S. (2020). The Strategic Role of the E-Tutor in New Learning Contexts. In *International Workshop on Higher Education Learning Methodologies and Technologies Online* (pp. 300-314). Springer, Cham.

Goold, A., Coldwell, J., & Craig, A. (2010). An examination of the role of the e-tutor. *Australasian journal of educational technology*, *26*(5).

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., & Tatham, R.L. (2014). *Multivariate data analysis* (7th ed). Pearson, Edinburgh Gate, Harlow, Essex.

Henrie, C.R., Halverson, L.R., & Graham, C.R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education*, *90*, 36-53.

Kizilcec R.F., & Schneider E. (2015). Motivation as a lens to understand online learners: Toward data-driven design with the OLEI scale. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *22*(2), 6.

Kopp, B., Matteucci, M.C., & Tomasetto, C. (2012). E-tutorial support for collaborative online learning: An explorative study on experienced and inexperienced e-tutors. *Computers & Education*, *58*(1), 12-20.

Kovanović, V., Joksimović, S., Poquet, O., Hennis, T., de Vries, P., Hatala, M., Dawson, S., Siemens, G., & Gašević, D (2019). Examining communities of inquiry in Massive Open Online Courses: The role of study strategies. *The Internet and Higher Education*, *40*, 20-43.

Lentell, H. (2004). The importance of the tutor in open and distance learning. In *Rethinking learner support in distance education* (pp. 76-88). Routledge.

Li, S., Zhang, J., Yu, C., & Chen, L. (2017). Rethinking distance tutoring in e-learning environments: A study of the priority of roles and competencies of Open University Tutors in China. *International Review of Research in Open and Distributed Learning*, *18*(2), 189-212.

Massuga, F., Soares, S., & Luis Dias Doliveria, S. (2021). El papel del tutor en la enseñanza de la educación a distancia: una revisión sistemática sobre el enfoque de competencias. *Revista de Educación a Distancia (RED)*, *21*(66).

MacDonald, J. (2008). *Blended learning and online tutoring: Planning learner support and activity design*. Gower Publishing, Ltd.

O'Rourke, J. (2003). *Tutoring in open and distance learning: A handbook for tutors*. Commonwealth of Learning, Vancouver.

Paul, R., & Tait, A. (2019). Open Universities: Past, Present and Future. *International Review of Research in Open and Distributed Learning*, *20*(4), i-viii.

Perna, L.W., & Leigh, E.W. (2017). Understanding the Promise: A Typology of State and Local College Promise Programs. *Educational Researcher*, *XX*(X), pp. 1-26.

Price, L., Richardson, J.T., & Jelfs, A. (2007). Face-to-face versus online tutoring support in distance education. *Studies in Higher Education*, *32*(1), 1-20.

Rivoltella, P.C. (2017). *Tecnologie di Comunità*. Brescia: Editrice Morcelliana.

Rotta, M., & Ranieri, M. (2005). *E-tutor: identità e competenze. Un profilo professionale per l'e-learning* (Vol. 4). Edizioni Erickson, Trento, Italia.

Sannicandro, K., De Santis, A., Bellini, C., & Minerva, T. (2019). Analysis of completion and dropout rates in EduOpen MOOCs. *Italian Journal of Educational Research*, 27-42.

Schmidt, J.A., Rosenberg, J.M., & Beymer, P.N. (2018). A Person-in-Context Approach to Student Engagement in Science: Examining Learning Activities and Choice. *Journal of Research in Science Teaching*, *55*(1), 19-43.

Sottilare, R.A., Graesser, A., Hu, X., & Holden, H. (Eds.) (2013). *Design recommendations for intelligent tutoring systems: Volume 1-learner modeling* (Vol. 1). US Army Research Laboratory, Orlando, Florida.

Tait, A. (2003) Guest editorial-Reflections on student support in open and distance learning. *The International Review of Research in Open and Distributed Learning*, *4*(1).

Van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2015). Teacher regulation of cognitive activities during student collaboration: Effects of learning analytics. *Computers & Education*, *90*, 80-94.

Vegliante, R., & Sannicandro, K. (2020). The role of the tutor in the university context and in distance learning: an exploratory research. *Journal of e-Learning and Knowledge Society*, *16*(3), 76-85.