Feedback to align teacher and student in a Digital Learning Ecosystem

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Abstract

In this paper, we present an example of a Digital Learning Ecosystem, set up during the first period of the pandemic emergency and then remodelled and re-proposed for hybrid didactics provided afterwards, involving five pedagogical-didactic courses of two universities in central Italy.

The central device in this Ecosystem was recursive feedback, which in contexts of didactics mediated by screens can anyhow activate discursive, adaptive, interactive and reflexive dynamics.

In order to understand if these aims were pursued, we administered an open-ended questionnaire to 274 students, which was not intended to measure their enjoyment of the method and the environment, but their perceptions regarding the effectiveness of the system on their learning processes, not only at a cognitive level, but also on at an interpersonal and intrapersonal level.

The analysis was conducted according to the Structural Topic Model, which allowed us to re-read the responses as a unique corpus of reflective writings, generated by the students after the input provided by the assigned task.

Key words: Feedback; Digital Learning Ecosystem; Structural Topic Model; Students perception; Distance learning

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° The article is the result of a collective and interdisciplinary discussion. In detail: Maila Pentucci is the author of the chapters 1, 5, 6 and of the sub-chapter 5.2. Annalina Sarra is the author of the chapters 3, 4 and of the sub-chapters 3.2, 3.2, 3.3. Chiara Laici is the author of the chapter 2 and of the sub-chapters 5.1, 5.3. Annalina Sarra is also responsible for the methodological framework and statistical analysis of the data and she processed the images and tables. Maila Pentucci and Chiara Laici are responsible for the theoretical framework in the field of education studies and educational technologies and for the pedagogical-didactical interpretation of the results.

1. Introduction

In this paper we want to analyze the students' perception towards a learning-teaching experience led within a Digital Learning Ecosystem (Väljataga *et al*., 2020), designed in the period of the pandemic emergency and used also for the blended learning, activated in the following years.

The Ecosystem aggregated tools for synchronous and asynchronous social communication, a platform for synchronous interaction both in large classrooms and in groups and subgroups, digital repositories for downloads and uploads, collaborative writing tools, online polling tools. It supported and included teaching activities related to multiple learning approaches: by appropriation, by practice, by enquiry, by collaboration (Laurillard, 2012). Feedback between teacher and student and peer feedback were the processes that guided, supported and gave coherence to the system.

Specifically, we present the results of a survey, administered to 274 students from 5 degree large-courses in pedagogical and didactic disciplines, in two different universities in central Italy. Students expressed their perception in a text guided by questions, requiring the reflection and the clarification of their inner and deep thoughts on the Learning Ecosystem.

Considering the complexity of the context, the codification work, the analysis and the interpretation of data were led according to a multidisciplinary and hybrid approach, which saw the contribution of statistics, pedagogy, didactics, and semiotics. As we will discuss in the section on methodology, we used the Structural Topic Model (Roberts *et al*., 2013) to obtain a fully data-driven interpretative reading. This way the researcher can get detached from his intentionality and preconception, innate in the guiding-question tool, and focus completely on the answering students' perceptions, without being influenced by categories ex ante fixed.

The research hypotheses were formulated a posteriori, generated directly from the text. Thus, they reflect the representations embodied by the students. The results of the research were therefore discussed starting from the following issues, derived directly from the data collected and compared with the literature: a) the usability and perceived effectiveness of the digital learning ecosystem as supporting and guiding learning postures. b) The interaction and alignment between students and teachers, ensured by the feedback structures within the Digital Learning Ecosystem.

2. Background

According to previous research led on learning design in higher education (Laurillard, 2006; Weller *et al.*, 2018; Bonanno *et al.*, 2019), learning devices, where technological resources with a social and dialogic character were integrated and aggregated, enabling to enhance the alignment (Rossi, 2017) between the professor's goals and the students' ones. That happened through the activation of recursive feedback (Rossi *et al.*, 2018) that in contexts of didactics mediated by screens can anyhow generate discursive, adaptive, interactive and reflexive dynamics (Winstone *et al.*, 2016, Nicol, 2018; Laici, 2021). The dynamic feedback loop (Carless, 2019) is fostered and supported by learning environments inspired by the principles of adaptation and congruence (Maturana and Varela, 1980): this enables to hybridize some tools, thought especially for didactics, through generalist tools, reconverted to the uses and the educational needs. In this sense the environment becomes a layout, a space for the convergence (Jenkins, 2006) where old and new media collide and work together, experiences that are a bridge, personal and collective meanings (Garavaglia, 2006). According to recent studies (Carrillo and Flores, 2020; Pereira *et al.*, 2021), to foresee a positive teaching-learning process in distance situations we must consider the following aspects: 1) the socialization and the possibility of working in cooperative environments, developing relationships not only aimed at studying. 2) The possibility of co-building knowledge in an active way, within a community of practice. 3) A suitable didactic design supporting learning and enabling the alignment.

Open, hybrid learning environments governed by feedback processes can be defined as Digital Learning Ecosystems (Rossi and Pentucci, 2021). Technologies in didactics are not simply tools improving what already exists, but they have a value as they enable to re-think education and educational models, «if we think about technology in the context of an ecology of learning environments» (Fishman and Dede, 2016, p. 3).

A Learning Ecosystem (Kramer, 2007; Jeladze *et al.*, 2017; Guitierrez, 2008; Gütl and Chang, 2008) is an adaptive socio-technical system populated by digital species (tools, services, resources) and by social agents (students, professors, technicians) that mutually interface, reproducing what happens within a biological ecosystem. As known, in the biological ecosystem, two components interact: the biotic one, made of living organisms that are the different species, and the abiotic one, made of the elements of the environment, that is soil, temperature, light and others.

Highlighting the contribution of technology, the Digital Learning Ecosystem (Pentucci and Laici, 2020) is considered a strongly transformative environment, within which the contribution of technologies is essential in the

dynamics that are typical of learning that foresees the breaking of previous balances and the search for new ones. It is an environment open to new hints coming both from the outside and from the inside, flexible and able to answer in a resilient way to future distresses (Väljataga *et al.*, 2020).

3. Materials and methods

This paper benefits from the use of open-ended survey questions that can better capture respondents' learning experience in their own words. In general, researchers consider open-ended survey questions useful tools for identifying concepts and perspectives on which they know little about (Roberts *et al.*, 2014; Schuman, 1966, Pietsch and Lessmann, 2018). However, despite potentially bringing valuable insights, for practical reasons, surveys tend to restrict themselves to closed-ended responses, since qualitative open-ended questions require, in fact, an intensive workload for coding and analyzing (data resulting from unstructured texts. Over the last years, the literature has sped up the analysis of open-ended responses, suggesting a group of text-mining techniques for the automated content analysis on unstructured survey responses. To address our research question, in this paper, we use a text-mining tool, known as Structural Topic Model (STM). STM, developed by Roberts *et al.* (2013), is very similar to Latent Dirichlet Allocation (LDA) (Blei *et al.*, 2003), allowing each document (e.g. response to the open-ended question) to consist of multiple topics, with varying degrees of memberships between documents. Anyway, STM takes the traditional LDA topic model, one-step further, by incorporating document metadata into the topic estimation. In the next section, we provide a technical overview of LDA and STM models.

3.1 Topic modelling: LDA and Structural Topic Models

Numerous methods, branched off from the subject area of "generative probabilistic modelling" (Liu *et al.*, 2016), and embedded under the umbrella of "topic modelling", have been developed to accomplish the task of determining what events or concepts a text document is discussing. Differences between models and their underlying algorithms can be explained by taking specific relationships and structures into account, such as short text (Yan *et al.*, 2013), long-term sequential data (Blei and Lafferty, 2006), highly correlated data (Lafferty and Blei, 2006), and data with complex structural relationship (Li and McCallum, 2006).

One of the earliest and more frequently utilized computational analysis techniques for investigation of the theoretical structure of a collection of textual

data is the Latent Dirichlet Allocation (LDA), first developed by Blei *et al.* (2003). LDA attaches topical contents to text documents, by assuming the existence of hidden variables (topics) that explain the similarities between observable variables (documents). Each document arises as a random mixture of K latent topics: that is each document has a probability of belonging to each topic. In the LDA approach, documents are generated via a 3-level hierarchical Bayesian structure, under which each document is modelled as several topics and each topic is modelled as a set of words. To be aware of the core idea of the algorithm, we set up the following notation. Let the documents in the given corpus be denoted by $d\_i=(w\_i1,\dots,w\_(in\_i))$ of length $⟦n⟧\_i$. Each word w_ij comes from a vocabulary, which consists of V different terms. The term distribution for each topic is modelled by a Dirichlet distribution $β\_i\sim$ Dirichlet (η). The proportion of topic distribution for each document is distributed as $ω\_i\sim$ Dirichlet (α). Each word w_ij is associated to a topic z_ij which follows a multinomial distribution $z\_ij\sim$Multinomial ($ω\_i$). The number of topics K is fixed and specified in advance. Likewise, the Dirichlet hyperparameters η and α are determined prior to modelling. The LDA algorithm uses the Gibbs sampling technique for Bayesian inference (Griffiths and Steyvers, 2001). Estimates of model parameters provide researchers with data on what the topic will look like. Specifically, analysts gather data on topic representation within each document and within the corpus and on the words most associated with each topic, having in such a way the possibility to ascribe intuitive meaning to the topic. LDA is a "bag of words" model, this implies that documents are modelled as finite mixtures over an underlying set of latent topics inferred from correlations between words, despite of word order. Additionally, it is worth noting that the LDA algorithm relies on some restrictive assumptions. Firstly, topics within a document are independent of one another. It follows that knowing that document 1 has a latent topic 1 does not add any information about whether the document has latent topic 2, 3, etc. Secondly, the distribution of words within a topic (i.e. topic content) is stationary. Said differently, topic 1 for document 1 uses identical words as topic 1 for document 2, 3, and so on. Finally, LDA only looks at the text of the document when determining topics, and does not consider any other information: topics can be modelled entirely based on the text of the document.

In this research, we selected the Structural Topic Model (STM), which extends the LDA framework by allowing covariates of interest to be included in the prior distributions for open-ended responses-topic proportions and topic-word distributions. While in LDA, topic prevalence and content come from Dirichlet distributions with hyperparameters set in advance, with STM, topic prevalence and content come from information about the document or about the respondent. Accordingly, a key feature of STM is its ability to use

document-level information or covariates to explain differences in prevalence (proportions of different topics that occur within documents) and topical content (probabilities associated with words in each topic) between documents. These characteristics of STMs make it a suitable method for analyzing textual data from open survey questions. Similar to LDA, STM is also a probabilistic generative model that defines a document generated as a mixture of hidden topics (see Fig. 1, in image annexes).
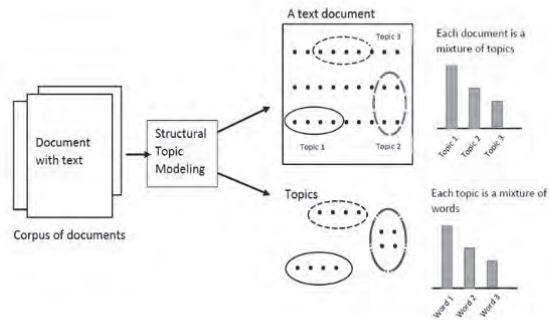

Fig. 1 - Schematic of STM algorithm - Adapted from "Detecting latent topics and trends in educational technologies over four decades using structural topic modelling: A retrospective of all volumes of Computers & Education" by Chen, Zou, Cheng, Xie, 2020, Computers & Education*, 151, p.5. Copyright 2020 by Elsevier.*

In the STM, topic proportion can be correlated, and the prevalence of those topics can be influenced by some set of covariates X through a standard regression model with covariates $\omega \sim LogisticNormal(X\_\gamma,\Sigma)$.

According to Robert *et al*. 2014, the next step in the STM algorithm is to replace the distribution over words with a multinomial logit such that a token's distribution is the combination of three effects (topic, covariates, topic-covariate interaction) operationalized as sparse deviations from a baseline word frequency (m). The interested reader can find an exhaustive description of this topic model in Roberts *et al*. (2013).

3.2 Data pre-processing

To prepare data for text-mining analysis and increase the interpretability of the latent topic in the data, we undertook some pre-processing steps.

Corpus preparation and cleaning were done using the quanteda package (Kenneth *et al.*, 2018) in R (R Core Team, 2022), that provides stop-word

removal, stemming, lemmatizing, tokenization, identifying n-gram procedures, and other data cleanings, like lowercase transformation and punctuation removal.

In order to improve the performance of information retrieval, we first carried out stop-word elimination, that is we filtered out words, such as articles, prepositions, conjunctions, common in any language, that are not helpful and in general usable in text mining because they do not contribute to words' contextual meanings or the identification of topics. Then, we reduced words to their root form (stemming) and removed inflectional endings and returned words to the base or dictionary form (lemmatization). Stemming and lemmatization are traditionally used in information retrieval systems to make sure that variants of the word are not left out when text is returned and identify a canonical representative for a set of related word forms.

The pre-processing steps are completed by dividing a text input into tokens, like phrases, words or other meaningful elements (tokenization) and detecting sequences of two or more lexical units whose co-occurrence is higher than a given threshold (n-gram procedures).

Finally, we applied a commonly used term-weighted methods called TF-IDF (Term Frequency-Inverse Document Frequency) to score the importance of a word in any content from a collection of documents based on the occurrences of each word, and it checks how relevant the keyword is in the corpus. Thus a pre-filtering stage with STM, as well as any topic model, is a vector space model (Salton *et al.*, 1975), also called document-term matrix. In a document-term matrix, each row represents a document, each column a term and each cell value is the term influence in the respective document.

3.3 Model extimation and search

To avoid any possible inconsistencies, we carried out our topic analysis on the original texts, expressed in Italian.

We used the **stm** package (Roberts *et al.*, 2019) to conduct our analyses. To estimate the STM we performed an exhaustive search of the number of topic K. Determining the number of topics is one of the most difficult questions in unsupervised learning. In this respect, Grimmer and Stewart (2013) observe that there is no correct number of topics that is appropriate for any given corpus, while Roberts *et al.* (2014), stress how the variation of the K number of topics is associated changes in the "level of granularity of the model's and in the researcher's view into the data".

Choosing the appropriate number of topics requires a combination of diagnostic measures and the researcher's judgment and expertise.

For the corpus analyzed in this paper that consists of 1354 documents we

run four candidate models, varying K from 5 to 20, incrementing by 5 using the search K function of the stm R package.

Through the search K function, we quickly looked at some metrics, namely held-out likelihood, residual analysis, lower bound and semantic coherence. Fig. 2 contains a depiction of each metric across the various solutions.

Optimal results would demonstrate relatively high semantic coherence, low residuals, a maximized lower bound, and a high held-out likelihood.

Held-out likelihood and residual analysis give a good understanding of the model fit, whereas semantic coherence focus on the quality of the topics. Semantic coherence is maximized when documents have a high internal consistency: that is the most probable words in a given topic frequently co-occur together within documents. This measure is closely related to human judgments of topic quality (Mimno *et al.*, 2011). Semantic coherence alone is relatively easy to achieve, since models with less topics tend to be characterized by high semantic coherence scores. As a counterpoint, Roberts *et al.* (2014) suggested using also the exclusivity measure that looks at the distinctness of topics by comparing the similarity of word distributions of different topics. Triangulate all diagnostic measures can be rather challenging. In particular, the choice of a model based on semantic coherence and exclusivity is a matter of trade-off because these metrics tend to be anti-correlated. In Fig. 3, we provided the exclusivity-semantic Coherence plot for candidate models with 5, 10 and 15 topics. We argue that most of the topics within model 10 are of uniform quality, because they are less dispersed across the two sematic coherence-exclusivity dimensions. Furthermore, checking the held-out likelihood that assesses the model's prediction performance we observe that it is optimal in 10 topics. It follows that the 10-topic model was settled as the best option.
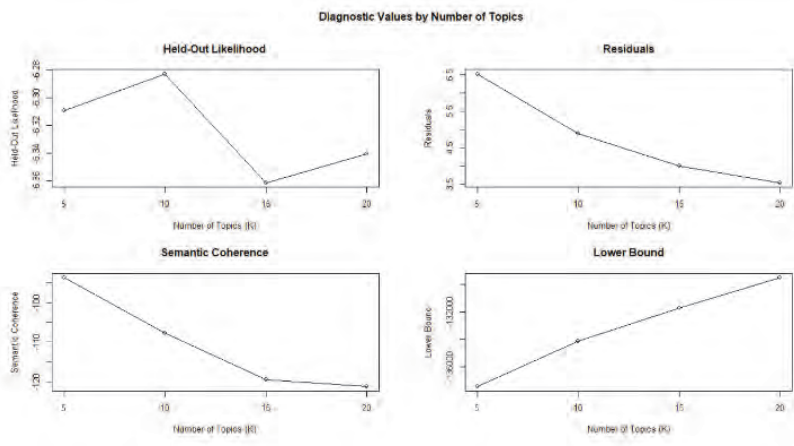

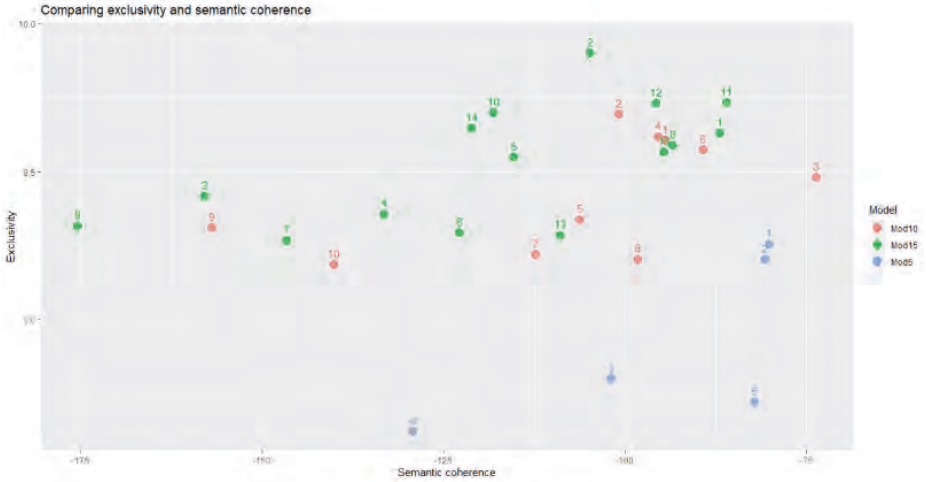*Fig. 2 - The relative goodness of fit for topics spanning 5, 10, 15, 20*

Fig. 3 - Exclusivity-Semantic Coherence Plot for candidate models with 5, 10 and 15 topics

4. Results: topics interpretation

The validation of topic output requires the additional step of attaching meaningful labels to estimated topics that describe the essence of each of them.

For interpreting and labeling the topics, we first display the words with the highest probability for each topic (Fig. 4).
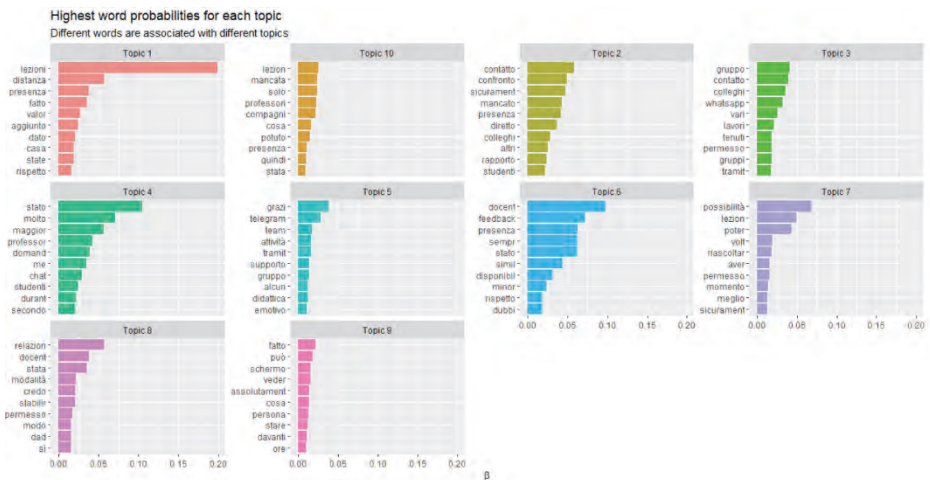

Fig. 4 - Highest word probabilities for each topic

Although the terms shown in Fig. 4 have the highest probability of occurring conditionally in the topic, the terms may not be semantically interesting (Kuhn, 2018). Equally important in determining a word's semantic content, is, in fact, the exclusivity of words to topic (Bischof and Airoldi, 2012).

Accordingly, we also paid attention to the frequent and exclusive words for each topic (hereinafter, FREX), defined as the ratio of term frequency conditional in a topic to term-topic exclusivity (Roberts *et al.*, 2013, 2014).

The FREX metric is a harmonic mean of the two dimensional summary of each word's relation to a topic of interest that tries to locate terms which are both frequent in and exclusive to a topic. Similar to FREX is the LIFT metric that gives higher weight to words that appear less frequently in other topics (Taddy, 2013). LIFT weights words by dividing by a word's frequency into other topics. Finally, we consider the SCORE metric that weights words by the log frequency of a word in a topic divided by the log frequency of the word in other topics. All these metrics are displayed in Table 1 (in annexes[1]).

We can also interpret the meaning of topics by reading in full the documents that are highly associated with each topic. Table 2 (in annexes) provides a sample of original representative comments for each topic.

Retrieving documents highly associated with each topic and parameterizing the themes in terms of both frequent and exclusive words allowed us to map the topical content of the corpus as follows.

Our examinations of documents associated with Topic 1 and top words (lessons, distance, comfort) showed that this topic involved the value added by online teaching. Accordingly, we classified Topic1 as topic on Physical space/home.

Looking at the set of words linked to Topic 2 (contact, confrontation, absence, presence, direct) and the correspondent documents, we were able to interpret this topic as "Lack of direct confrontation and relationship". Similarly, evidence shown in Table 1 and Table 2 supports the interpretation of Topic 3 as "Building the community: use of whatsapp". Topic 4 groups terms and documents related to the "Ask questions to the professor" while terms immersed in Topic 5 refer to the missing word of online learning platforms and we termed it "Communication and learning tools". The terms assigned to Topic 6 highlight how the teacher's feedback has not changed during the transition from face-to-face teaching methods to online mode. Accordingly, we named this theme "Feedback". Examining the main words that have the highest probability under Topic 7, we found out that it was highly associated with the topic words: "lesson", "be able" "reassert" "recorded". Thus, we interpreted Topic 7 as a topic on "Listen to the recorded lesson again".

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[1] Annexes at this link.

Reading the top words and the documents related to Topic 8, such as "relationship" and "teacher" we can term it as "Interaction with teacher".

On inspection of the last learned themes (Topic 9 and 10), we observed that there are less focused words that together are not always associated with distinguished topics.

We also estimate correlations between topics. If documents are prone to be dominated by a single topic, we would anticipate that the prevalence of most topics would be negatively correlated with one another. Conversely, topics that exhibit positive correlations are likely to be discussed together in a document. Conjoint inspection of the correlation graph and correlation matrixreveals that Topic 1 (Physical Space/Home) was likely to be discussed together with Topic 7 (Listen to the recorded lesson again). In the present study, we also found that Topic 4 (Ask questions to the professor) and Topic 6 (Feedback) on one side, and Topic 3 (Building the community: use of Whatsapp) and Topic 5 (Communication tools), on the other side, are likely to appear together in an open-ended response. Our quantitative analysis of textual data from open-ended survey questions is completed by assuming that topical prevalence is not constant across open-ended responses but influenced by some covariates.

Here, we use "teacher" as a covariate to explain differences in topical prevalence across documents. The regression results support the casual impact of "teacher" variable that especially affects how Topic 2, Topic 5, 6 and 7 vary by each document. Findings from these analyses are contained in Table 3 (in annexes).

5. Discussion

As we previously outlined, we discussed and analyzed the data from a pedagogical-didactical perspective, trying to make sense of students' perceptions regarding two main aspects:
a) The usability and perceived effectiveness of the digital learning ecosystem as supporting and guiding learning postures.
b) The interaction and alignment between students and teachers, ensured by the feedback structures within the Digital Learning Ecosystem.

The students' perceptions can be aggregated in three macro-themes: perceptions related to the postures of learning, perceptions related to virtual relationships and communication, perceptions related to feedback.

5.1 Learning postures

Topic 1 was called "Physical Space/Hom"e bearing in mind both the words

with the highest probability in the topics. Some of the top words (value, comfort, moving) make us understand what influence the Digital Learning Ecosystem has on the listening, attention and participation postures of students. The students underline that following the lessons from home enabled them to widen their class attendance, being free from having to move. This aspect enables to stretch the same concept of access and participation and it has to be considered as an element of inclusion.

Some students can concentrate more at home due to the silence, while others say that they have more distractions at home or in a working environment that is not very quiet or reserved, and still others emphasize aspects related to the digital divide.

An environment that is not specifically designed for training and education like the home one requires specific attention by the students that have to suit it themselves and it requires, therefore, a greater responsibility by the students that have to undertake a proactive and more independent attitude (Rivoltella and Rossi, 2019; Rivoltella, 2021). Another element of reflection concerns the possibility of greater interaction and participation during the online lessons for the shyer students; they, in face-to-face situations, feel embarrassed to speak. Instead, they interact if they can write (via chat or comments) or if they can intervene with only their voice, with the camera off and not exposing their face and bodies. (“*I wasn't seen but just read, I wasn't judged by my aspect nor my voice, but for my content*” “*I don't think that in a face-to-face lesson I would have intervened as I did in the online lessons*”).

Topic 7 (“Listen to the recorded lesson again”) shows us a posture activated by students thanks to the affordances of the digital ecosystem, linked to top words, *listening again, watching again, recording*.

The students consider as positive the possibility of listening again to the lesson and of watching it more and more times, getting back to it in a recursive way a long time and in different moments, being able that way to “deepen and complete their notes”, “clarify some points that weren't clear and reconsidering the most difficult parts of the lesson” or to retrace some passages that they had missed during the live lesson, to “recollect the missed concepts”. In this situation, the contents are always available, they can be used also in mobility and the timings of education widen and spread along the day with no space and time boundaries (Rivoltella, 2021). The risk of an excessive emphasis by the students on the possibility of having access to video-recorded lessons is, in fact, that of a passive use of the video-lesson. In fact, the student concentrates mainly on the proposed contents “not to miss anything” of what the professor said, putting on the second level the activation of reflexive and critical paths. In such a way, students emphasize an approach inspired by a transmissive and reproductive paradigm of knowledge where there is some well-defined

knowledge the professor has to transmit and the students have to accordingly reproduce.

5.2 Virtual relationship

Topic 2 was called "Lack of direct confrontation and relationship". The students think that interaction is somehow limited and lessened in the screen mediated mode. One of the extracted documents is particularly meaningful as the student states: "I feel sorry for not having had a physical space for being able to perform a teamwork". As far as the digital devices could foresee different possibilities of interaction and exchange and would guarantee even virtual spaces for cooperative learning led by a professor, the students, when online, perceived a great difference in building a community of learning, « A community of which the student becomes a legitimate and aware member, through an increased identity (of the self/I through the us/we) that gives him social consciousness, sense of responsibility, initiative, critical skills, solidarity» (Varisco, 2002, p. 96).

Reading that the "face-to-face contact both with the peers and the professor lacked" is meaningful: evidently the filter of the screen was perceived as a barrier that even though enabling them to see each other and talk to each other, interrupted the relational flow that used to be experienced in a classroom. As Rossi (2016) states «the characteristics of the digital modified the ways through which human activity operates and is conceptualized. […] It increases the distance between the individual's operating on the artifact and the intervention of the artifact in the world» (p. 12). The students, when explicating a physical and face to face contact perceived as lacking, talk about the disappearance of the body in the communication flow and do not perceive a new form of involvement due to the absence of mediation between user and medium, as stated by Fedeli (2016).

Topic 3 shows the attempt the students made to rebuild the community or at least the perception of the contact with the other, the sense of the group. The fact that the students brought within the educational ecosystem an unforeseen tool seems meaningful, that is the App WhatsApp, through which they performed their private conversations, through which, as we read in one of the extracted documents, the students kept in touch by "supporting and helping one another".

Topic 5, called "Communication and learning tools", confirms what is written above and as a matter of fact the correlation to Topic 3 is evident in terms of statistical analysis. In this case the perception shifts from the single tool to the whole ecosystem, which is identified by the students as essential in supporting not only learning in a particular and unusual situation, but also as a

space for discussion ("it is very useful to meet and to know each other better, through videoconferencing", for socializing "I had the chance of meeting new people that otherwise I wouldn't have met", of emotional support "I created a WhatsApp group together with other 7 girls for didactic end emotional support").

5.3 Feedback

Topic 4 was called "Ask questions to the professor", the meaningful words associated with it (questions, asking, available, greater, professor) recall in fact the possibility offered to students to constantly ask questions to professors, welcoming the students' doubts. Through this Topic it is underlined that, in an environment centered on feedback, undertaking a dialogic attitude is fundamental for the professor designing in the lesson some specific moments of interaction during which the students can speak and get activated. The students highlight how such an aspect enabled them to go beyond distance ("Notwithstanding the distance I perceived the professor as very close to us students"). Besides, students underline how the availability to dialogue established both specific listening moments for the individual student "the added value was being able to get in touch with her at any moment, almost like having private lessons, aimed at clarifying any single doubt", and moments for the class group, to support the whole learning community. This enables to rethink about the importance of the "presence" of the professor in those online environments and his declination in cognitive, social and facilitating presence (Rapanta, Botturi, Goodyear, 2020).

Topic 4 is particularly linked to Topic 6 where the centrality of interaction and specificity of feedback returns. The presence of this specific Topic makes the importance of feedback as a constitutive element of the educational path come to the surface. It underlines the alignment with the professors' goals, who intentionally designed a digital learning ecosystem oriented to recursive, dialogical, transformative feedback, centered on the learning process (Winstone and Carless, 2019; Laici, 2021). Despite the emergency situation that required a change in teaching methods, the possibility of giving and receiving feedback was not compromised. In fact, students have noted that the quality of feedback they received was similar to what they would have received in a face-to-face setting, and in some cases, even better. "The professor's feedback wasn't lessened, rather it was increased. He made himself available for our doubts". In other cases students signal that the peculiar situation contributed to generate shorter feedback in comparison to the one that could be heard in person. The feedback that makes use of different tools becomes a multi-channel one. It punctuates communication and educational events in a progressive way

enabling the students to activate themselves and to look for some feedback, the feedback that tries to overcome the classic approach of "feedback as telling" (Sadler, 2010) to be oriented instead towards a true process centered on learning.

6. Conclusions

The complexity and fluidity of contemporary educational contexts, which have become greater in moments of crisis by the outlining of new hindrances and limits, require a revision and a re-thinking at a global level of the learning-teaching practices.

One of the perspectives that can be useful to make the investigation meaningful is that of hybridization. We surely need to hybridize educational environments, rethinking the concept of Blended learning in a wider meaning. Vertical blended, which foresees an alternation between moments of classroom didactic activity and moments of distance one, has to be sided by a horizontal blended, which integrates and hybridizes real and virtual, analogical and digital in a synchronous dimension and at the same time that foresees a connection between different timings and spaces. Not only between school time and space and personal time and space, but also between other different spaces, both public and private, which generate learning occasions and that have to be systematized within ecosystemic dimensions.

In the same way, the mash-up between tools that were not developed for didactics, but also generalist ones re-positioned in contexts and for different uses, offers simplex solutions able to face problems that are difficult to decipher, enabling the use of what is known and habitual in unusual situations.

In a panorama that requires change and innovation, it is also advisable to hybridize both research and analysis in relation to those experiences: the meeting and the dialogue between different subjects, between different investigation perspectives, as the one realized in this project, can indeed bring to the surface some results that are not visible to a single site. In this case, it was possible to interrelate the strict rigorous methodology of statistics and the deepness of pedagogical-didactic analysis. The different expertise of the researchers have grasped and analyzed the data both from the quantitative and the qualitative point of view, in an approach that can be defined as mixed (Creswell, 2015) and have fine-tuned a way to investigate the perceptions and the thoughts of a great number of individuals in comparison to didactic facts, which could be fine-tuned again and re-used in following researches.

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