Learning Time Patterns: Many Study Times To Consider When Designing Digital Learning

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***Abstract*—One of the most important issues in digital learning is understanding the time dimension and its impact on the design and study of different teaching methodologies. This paper analyses learning time from user data to identify the relationships between performance, methods used and the characteristics of learning materials. This paper investigates aspects oflearning time for three different methodologies: smartlearning; videolearning; tutorial-storytelling. The analysis shows that tutorial-storytelling is an appropriate and effective methodology from multiple perspectives; smartlearning does not guarantee completion or an adequate study pace and uses time; videolearning is positioned in an intermediate level: it performs well, with a more than satisfactory results, but in the face of more difficult and strenuous study, so there is ample room for improvement in this type of course from a technical and a purely methodological point of view.**

***Keywords*—Learning KPI; Learning Times; Digital Learning Design**

I. INTRODUCTION

Learning time is a key factor in any training project. In particular, it is crucial in digital learning and all self-led learning projects. In addition, study time also drives in the digital content market, just as it does for the enjoyment of in-depth content (e.g., estimated reading time in newspaper articles, time listening to an audio or viewing a video) and is at the same time also a factor in motivation and engagement. However, there are many dimensions of time in an online course to be taken into account and better investigated (Figure 1):

- technical time, i.e., the running time of an instructional resource measured in minutes/hours;
- organizational time, i.e., availability of teaching resources (time of course opening);
- individual study time (dedicated time) overall and per session, also related to personal characteristics (learning style), availabilities, engagement, and reporting time;
- learning time (related to understanding and acquisition of content);
- commercial time (standard duration).

Therefore, effectively designing the time of a course and defining access rules is a nontrivial problem for the instructional designer.

Another emerging theme is the diversity between intrinsic study times and those provided by teaching materials in different methodologies. Video learning, webinars, and digital materials involve different instructional dynamics specific to each methodology. Investigating time differences means being able to give instructional designers clearer information to design teaching, taking into account cognitive load and usage patterns of training materials. In Section II we briefly review models of learning times in literature. In Section III we describe the courses' data and the methods of analysis. In the following Section IV, we will describe our main results on learning time patterns. Finally, in Section V, we will present our findings and some lines for future works.

Figure 1: The different dimensions of time.

II. THE DIFFERENT TIMES IN LEARNING

Time is an essential variable to be investigated in understanding learning processes, as it is an important predictor of learning outcomes. However, it is still little studied [1]. Time patterns are crucial to understanding the factors contributing to effective learning. As collected by Cortès et al.[2], several studies assess the impact of time on:

- outcomes: group exercises or discussions/sharing tend to improve training outcomes [3]. Outcomes include both satisfaction and knowledge acquisition;
- satisfaction: time use is a factor in measuring satisfaction with a course [4][5];
- learning: participants who devote adequate time per week to study have better satisfaction. Knowledge transfer is associated with time spent online per day studying.

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Participants who spend more time daily online (social and internet) have more significant levels of learning. Then time spent on academic tasks during the day is associated with more learning (mainly using the morning hours). More digitized users (more hours online) have skills in applying knowledge to different contexts (both academic and work) [2].

According to [6], learning is related to prior experience with distance learning, individual preferences, and average study time. More interest has been devoted to analyzing study hours over available time. Time-of-day (TOD) is a valuable key to understanding differences in use/access to courses and devices.

Some studies delve into learning time patterns, using instructional conditions [7], i.e., the way courses are delivered and the level of autonomy or individual organization [8]. Stockwell [9] highlights how students use different study modes based on other times of the day and devices used. For example, Casany et al. [10] highlighted the greater use of mobile devices at night.

Sher et al. [11] point out that the study and the modes used to depend on the time of day it is carried out. In particular, there are better results for students who used different methodologies to perform the assigned tasks (with a predominance of computer and intensive learner type). Intensive learners, such as users with little use of technology, did not show significant differences in study days but significantly different results. The study showed that computer use for students is related to a meticulous mode of study [9] compared to mobile service for tasks that require precision. Students who used multiple study modes and tools tended to use them during the daytime, preferring the computer during nighttime hours. Online study sessions are primarily performed in the afternoon for all students [10], identifying this behavior as related to students' commuting hours on campus.

The temporal dimension is, therefore, a source of information about learning patterns that can help support learners and improve the accuracy and reproducibility of the predictivity of learning outcomes [1]. These studies are also critical to understanding how to design learning paths, test the most effective and agile teaching methodologies based on content, and make the use of time explicit for the learner to equip themselves with strategies for effectiveness and efficiency in studying.

From the perspective of content creators, the time concerns the commercial duration of the courses and the availability of the license. It follows that it is essential to make explicit all dimensions of time in training to effectively govern this variable in the different steps of the life of an online course. Therefore, time is a very complex variable composed of different measures.

A comparative examination between teaching methodologies of adequate study time (i.e., related to passing final tests) is proposed in this article to investigate whether different patterns of time of use, behavior, and performance are present, the latter analyzed with the LearnalyzeR tool [12]. The findings will be helpful in both the design and organizational phases.

III. Data and methods

The study involved a sample of different methodologies courses on a client's (insurance company). The courses are delivered over the past year. The data are representative of the types of courses listed in the Piazza Copernico srl catalog.

The teaching methodologies analyzed were:

- **Videolearning**: an effective type of Digital Learning Course designed according to various levels of complexity. Divided into two groups:
  - *Graphic videos*, very suitable for explaining short concepts clearly and simply and creating stories. More or less sophisticated graphic input depending on the client's needs.
  - *Teaching Pills* (videos with actors)video-Lessons with a lecturer or actor playing a lecturer, made at a desk, or otherwise with static filming.
- **Smartlearning**: particularly useful for print and offline study. The development involves transposing the client slides onto SCORM content pages plotted within LMS, using special authoring tools, with an accompanying narrative voice created by a professional (multimedia) speaker.
- **Tutorial_storytelling**: is mainly used for training and updating different types of content, technical manuals, description of procedures, and corporate information. Content pages come with text, images, graphics, and audio. The movement of elements on the page results from animated effects of graphics chosen from an internal library. Games with low-complexity interactions, test pages, and exercises also selected from a predefined internal library can be provided, taking into account customer needs and learning objectives. Similar is the Storytelling version suitable for training and updating on different types of content, soft skills, business processes, corporate reporting, regulations, and safety. This type involves a high level of multimedia, animation of objects and interaction types (SVG), case scripts, and stories that provide concreteness to the content covered.

Twelve courses of the same client of three different types were analyzed: smartlearning (5 courses for a total of 5 editions, 7052 users), tutorial_storytelling (3 courses for a total of 4 editions, 3545 users), videolearning (4 courses for a total 8 of editions, 5605 users); participants took the courses in the year 2022; the selection neglected editions with less than 10 participants.

Starting from the use of the LearnalyzeR tool [12], which analyzes critical issues by supporting tutor intervention on a day-to-day basis and divides the users of a course into performance classes, the present investigation turned toward the study of the Macro Performance Index (MIP) (composite index) by investigating its different aspects (sub-indicators): Results (I_R), Study Pace (I_{SP}), Course Structure (I_{CS}), Computer Adequacy (I_{CA}) (composite sub-indicators), and finally highlighting, with a descriptive analysis, the link between these indicators, time of use and course types.

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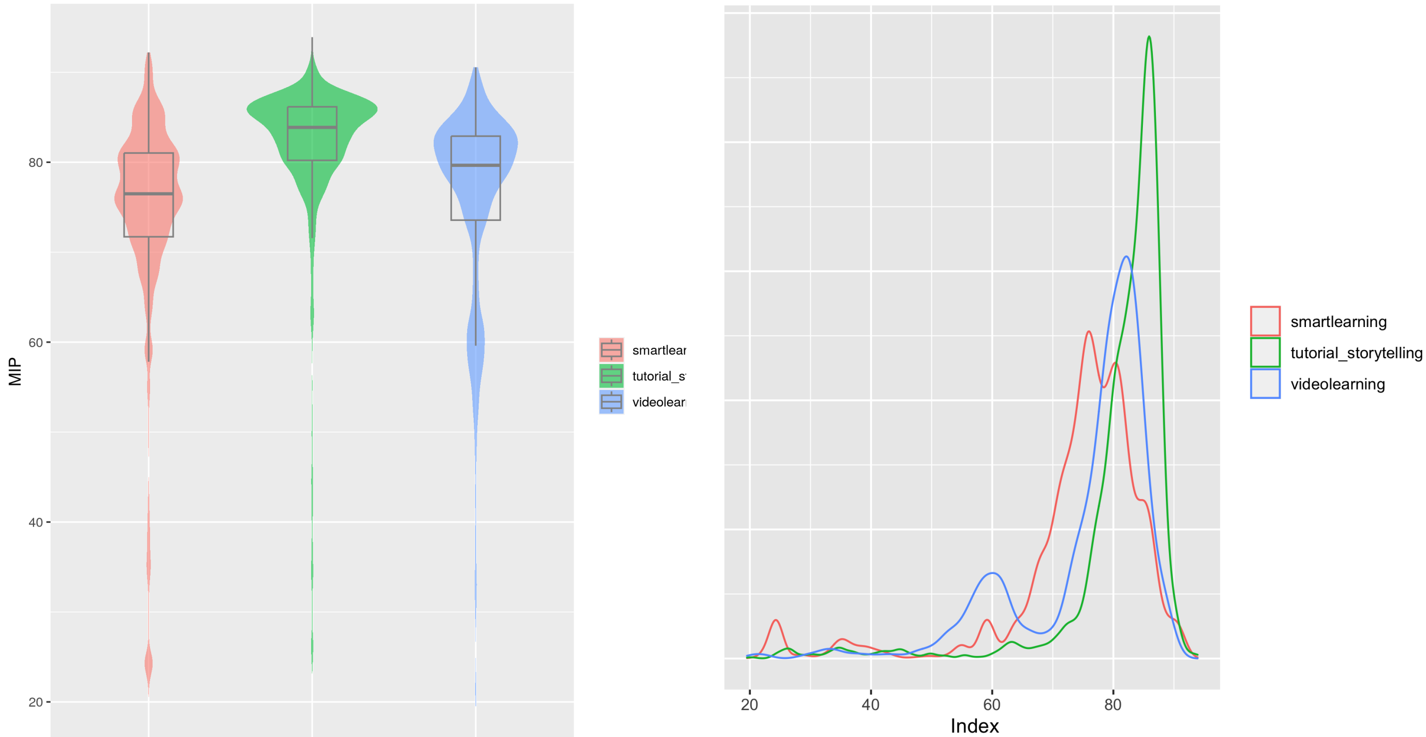

(a) Violin-Box-Plot

(b) Continuos Distribution

Figure 2: MIP distribution by course type.

As mentioned above, the LearnalyzeR tool calculates the MIP and divides users into performance classes: Lukers (MIP=[0;30)), Latecomers (MIP=[30;50)), Regulars (MIP=[50;70)), Hard Workers (MIP=[70;80)), Top Performers (MIP=[80;100]).

The performance index was constructed with the interaction of a group (panel) of individuals (experts) who identified all aspects (indicators) of the phenomenon (the perfomace); using the same method, a set of independent variables were identified for each indicator, which could be obtained from the platform data. Once the indicators and variables were defined, the weighted arithmetic mean was chosen as the aggregation function and the Analytic Hierarchy Process (AHP) [13] was used to calculate the weights. This method makes it possible to understand opinions on a specific topic without complicating matters for the respondent. By processing the answers, it allows the decision-making process of the weights to be constructed.

IV. Results

A first exploration analysis for the relations between MIP and courses type shows:

- **Smartlearning courses**. From Figure 2a, there is a broadened peak around 80 and a few pegs in the left tail (red line); analyzing Figure 2b, the MIP shifted toward performance values below 80, with a median at 76, so at least 50% of users have performance values below that; there is also a long tail down where at least 25% of users have performance below 71. In these courses, at least 50% of users are not at a MIP level above the Regulars class.
- **Storytelling Tutorial courses**. From Figure 2, one can observe a narrow peak above 80 (green line); in Figure 2b, the MIP shifted toward performance values above 80 (median 83) with a fairly homogeneous behavior of the population (narrow distribution); 75% of the users have performance between 80 and 86, so they belong to the Top Performers class.
- **Vidolearning courses**. From Figure 2a, one can observe different levels of performance: a narrow peak around 80 and a second peak around 60 (blue line); analyzing Figure 2b, the MIP is around 80 (median 79), and there is a consistent tail down; however, at least 75% of the users have performance above 73. In this type of course, despite the unevenness of performance, at least 75% of the users are above the Regulars class.

An exploratory analysis was carried out to identify the reasons for the observed performance by relating the sub-indicators, which constitute the MIP, to the type of course. The following was obtained:

Results (I_R)

- **Smartlearning**. From Figure 3, we observe a pronounced problem in the indicator I~R, the behavior of users for this indicator is uneven, and four main types of behavior

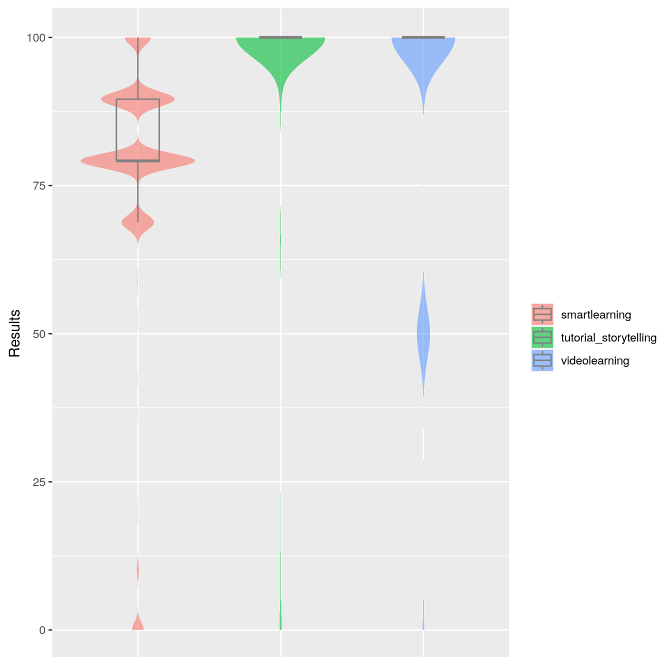

Figure 3: I_R distribution by course type.

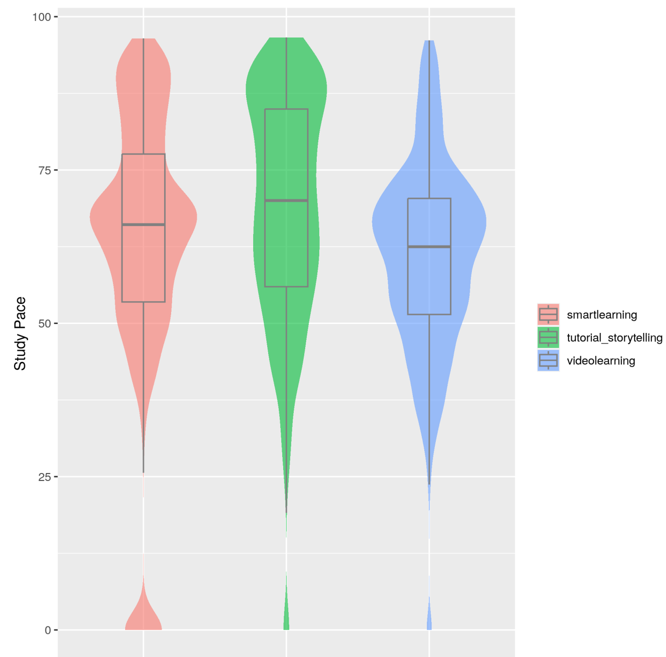

Figure 4: I_{SP} distribution by course type.

are presented. At least 25% of users have an IR indicator value of 79, and only 25% have a value above 89. Only a small number of users (about 8%) reach the value of 100; analyzing the I_R indicator [12], it is observed that this criticality is due to the variable course completion.

- **Tutorial_storytelling**.The participants have homogeneous behavior. At least 75% of the users have an I_R sub-index value of 100 (Figure 3).
- **Videolearning**. Participants have a rather homogeneous behavior. At least 75% of the users have a sub-index value I_R of 100; however, there is a tail downward at sub-index values around 50 (Figure 3), indicating a problem completing the course for a group of users (about 10%).

Analyzing the problems encountered in smartlearning courses for the indicator I_R shows that in all methods of this type, there is a completion problem. In all smartlearning editions, at least 75% of users do not complete the course. While in videolearning courses, there is a problem with one specific edition (361 participants) in which at least 30% of users do not complete the course. So in smartlearning courses, the characteristic of not completing is widely spread in the population under analysis. At the same time, for videolearning, it is a point problem with a single edition.

Study Pace (I_{SP})

From Figure 4, one can observe that:

- In **smartlearning** courses, the median of I_{SP} is 66 with a tail downward.
- In **tutorial_storytelling** courses, the median I_{SP} is 69 with a very elongated distribution structure, but at least 25% of the users have an I_{SP} value above 84 (3rd quartile).
- in **videolearning** courses, the median I_{SP} value is 66 with a tail downward, and only a small number of users have an ISP value above 75 (a tapering upward shape of the blue distribution), at least 75% of users have an I_{SP} value below 70.

All course types have a very uneven behavior for Study Pace, with values tending to the low end, more evident in videolearning.

The sub-indicator I_{SP} is highly dependent on the fruition time, the quantity we want to study. By analyzing the trend of fruition time concerning the expected time of the course structure, it is better to define the *Normalized Use Time* (**NUT** = fruition time/expected time) quantity. One can observe that all three types of the course show uneven fruition behavior (Figure 5), as for the I_{SP} index.

In particular:

- **Smartlearning**, at least 25% of users, in all editions, have a fruition time less than the time assumed in the course structure (the I quartile of NUT per edition varies between 0.7 and 0.9); at least 50% of the users have a fruition time equal to the time assumed in the course structure (median NUT for editions is around 1.02); finally, for two editions (of 516 and 1799 users) at least 25% of the users have a fruition time consistently greater than that assumed (3rd quartile of NUT between 1.6 and 1.7).
- **Tutorial_storytelling**, at least 50% of users have a time roughly equal to that assumed in the course structure (median NUT for editions varies between 0.9 and 1.2), but at least 25% of users have a longer time (3rd quartile of NUT between 1.8 and 2.0). The latter mainly concentrated on two courses (1619 and 1882 users).

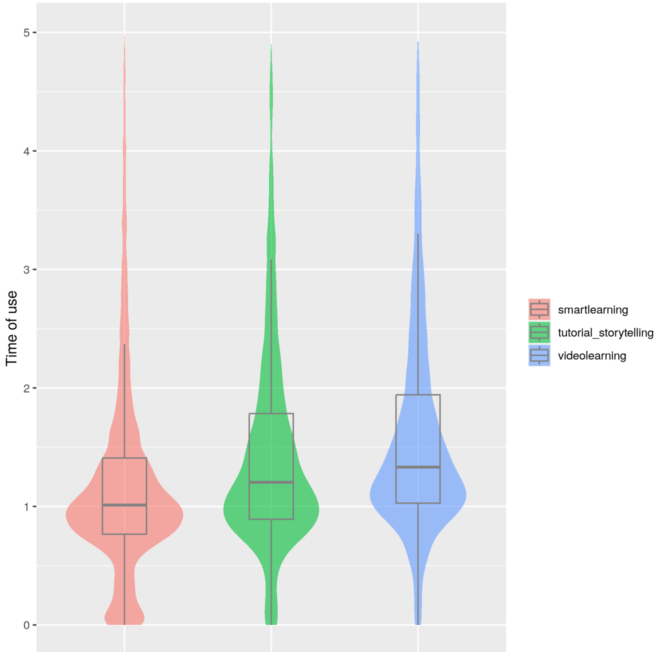

Figure 5: NUT distribution by course type.

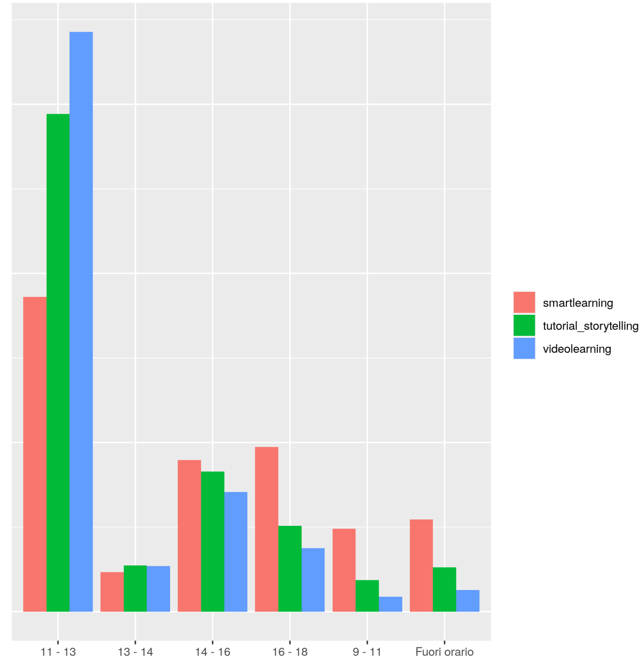

Figure 6: Distribution of connections by time slot and course type.

- **Videolearning**, at least 25% of the users, in all editions, have a fruition time roughly equal to the time assumed in the course structure (NUT varies between 0.9 and 1.2). In contrast, in two editions, the first quartile has NUT values between 1.5 and 1.7 (361 and 302 users, respectively). Looking at the median, 50% of the users have a NUT between 1.5 and 2.8; these participants are in 4 editions (11, 302, 361, and 2565 participants, respectively). For all editions, at least 25% of users consistently use more time than assumed in the course structure (3rd quartile of NUT between 1.6 and 4.3).

To summarize, in all course types, there is evidence of a long time in a significant percentage of the population. However, while it is present in smartlearning and tutorial_storytelling for a few courses/editions, on videolearning, it is widespread across all courses. Finally, in smartlearnig, it is observed that a substantial percentage have a shorter than expected completion time. This fits what was observed in the Results indicator analysis, as course completion is critical for this type of course.

For completeness of analysis, a view of the sub-indices Course Structure (I_{CS}) and Computer Adequacy (I_{CA}) by course type:

- The $\mathbf{I_{CS}}$ indicator in the **smartlearning** type has an identical value of 63 for all editions (medium complexity); **videolearning** also has a homogeneous complexity with I_{CS} between 50 and 57 (medium-low complexity), while the **tutorial_storytelling** editions have a very uneven structure of low complexity (about 55% of users take courses with an I_{CS} value of 39) and medium-high complexity (about 45% of users an I_{CS} value of 75).
- In **smartlearning** and **tutorial_storytelling** courses, there is a good **Computer Adequacy** (I_{CA} greater than 90), only 25% of the users with a value of I_{CA} less than 90 (1st quartile: smartlearning I_{CA}= 89, tutorial_storytelling I_{CA} = 84); while for **videolearning** courses at least 50% of users have I_{CA} values less than 89 and even at least 25% are below 79. The problems relate to linking and uploading videos; those critical issues are present in all the videolearning editions under analysis (except one).

Then, the analysis of the time slots and days of the week by course type give:

- From Figure 6 and Figure 7, for all course types, there is a utilization preference for the 11 a.m.-1 p.m. time slot (the off-hours time slot has a low, but not zero, link frequency), while there is no difference in link frequency for weekdays (holidays have a low, but not zero, link frequency).
- From the exploratory analysis so far, it can be inferred that the videolearnig course type has a criticality of a long time more evident than the other types because it is spread over all editions, with an issue related to linking and video uploading; in a subsequent analysis, it will be investigated whether and how these two criticalities are associated with each other. In contrast, the smartlearnig course type has a widespread completion issue across all editions.

Finally, a heatmap (Figure 8) is presented to get an overview of the above analysis. Looking at Figure 8, patterns between course types emerge:

- **Smartlearning courses:** all have the same complexity (always the exact value of I_{CS}), and, in general, users do

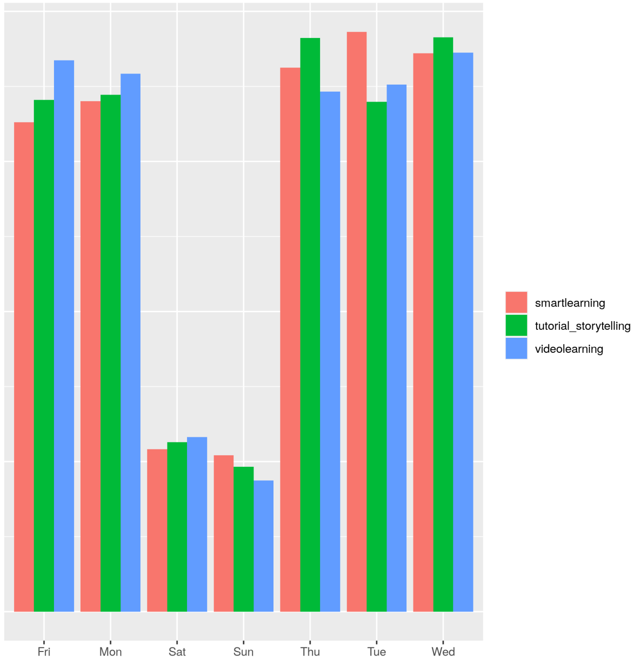

Figure 7: Distribution of connections by day and course type.

not have Computer Adequacy (I_{CA}) problems, but there are different patterns for Performace (MIP), Results (I_R), Study Pace (I_{SP}) and Normalized Use Time (NUT). Low values of MIP are found at dark I_R and I_{SP} (low values) and very dark NUT (less than expected fruition time); therefore, poor performance (MIP with low values) is a consequence of less than expected fruition time. There are bands where I_R and I_{SP} alternate between light and dark. There are good I_{SP} (light bands) at adequate NUT (fruition time around the expected time), but low I_R values (dark bands) or conversely low I_{SP} values (dark bands) at high NUT (fruition time much greater than the expected time), but good I_R (light bands). It can be concluded that to achieve the required results, it is necessary to have a greater fruition time than expected.

- **Tutorial_storytelling** courses users do not have particular Computer Adequacy (I_{CA}) problems, patterns of Performace (MIP), Results (I_R), Study Pace (I_{SP}), Course Structure (I_{CS}), and Normalized Use Time (NUT) can be seen. A very narrow band has low MIP values corresponding to dark I_R and I_{SP} (low values), a very dark NUT (fruition time less than expected time), and low complexity; this can be said to be punctual because this aggregate contains a small number of users. The most full-bodied aggregate is a trend of I_R with good values (users achieve the required results, clear band) but with bands in which I_{SP} and I_{CS} alternate between light and dark. It is possible to highlight that when there is low complexity (low I_{CS}, dark band), there is good I_{SP} (light band) and adequate NUT (fruition time equal to the expected time). In contrast, for more complex courses (high I_{CS}, light band), there are low I_{SP} values (dark band) and high NUT (fruition time much greater than the expected time). We conclude that the results can be achieved within the expected time when the complexity is low. At the same time, when the complexity increases, the required results are achieved by increasing the fruition time from one and a half times to more than twice the expected time.
- The **videolearning** courses have similar complexity (I_{CS}), but the patterns are more confusing. There are cases with low MIP values, despite good I_R corresponding to low I_{CA} and I_{SP} values and a high NUT; low MIP values, with low I_R values (dark bands) corresponding to adequate or too high NUT. In general, compared to the other course types, it is observed that NUT values are much clearer, thus a much longer than expected time of use and Computer Adequacy with problems (low values of I_{CA}).

In Figure 8, we can also observe dendrograms. On the left are aggregations of users by MIP level in the three-course types; at the top are the two aggregates of sub-indexes: I_{CA} with IR and I_{SP} with I_{CS}.

V. CONCLUSIONS

The analysis shows that **storytelling** is an appropriate and effective methodology from multiple perspectives, which performs best regardless of content and editions. One point of attention is the complexity of the structure directly related to the spent study time. It is also clear that smartlearning satisfies the needs for low time-to-market and low impact on the training budget, but it responds less well in terms of results achieved, with lower performance indices (MIP). The simplicity of the course, in terms of instructional design and methodological format, on the one hand,encourages the use of courses outside of working hours, but on the other hand, it does not guarantee completion or an adequate study pace and uses time. The risks associated with using smartlearning in training can be traced to potential problems with staff preparation and additional costs associated with necessary re-training.

Videolearning is positioned at an intermediate level: it performs well, with more than satisfactory results, but in the face of more difficult and strenuous study. In the unevenness of some of the data, there is ample room for improvement in this type of course:

- from a technical point of view, for example, the increasing enhancement of storage and delivery infrastructures for video content, both server-side and client-side, can make the Computer Adequacy values higher;
- from a purely methodological point of view, to manage the high value of uses time, instructional designs can distribute the “weight” of the topics and include more interactions, useful to scan the individual study time and create moments of self-assessment and knowledge reinforcement.

Starting from this analysis on the time issue in e-learning, always open and little explored on data, there emerges the need

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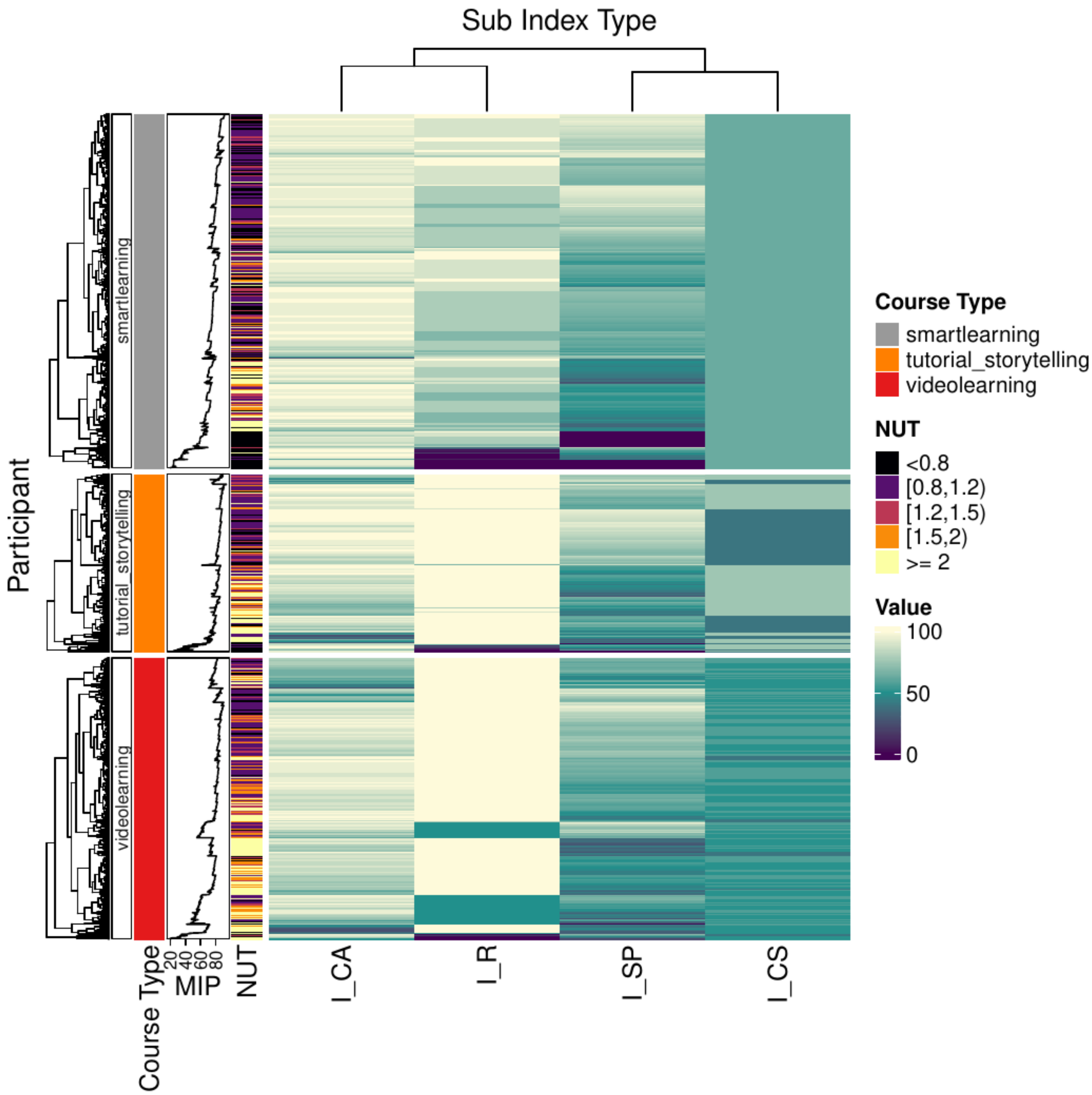

Figure 8: Heatmap. The quantities on the horizontal axis at the bottom are: Course Type (smartlearning, tutorial_storytelling, videolearning); Macro Index of Performance (MIP) is a continuous variable; the scale grows from left to the right, so the (left) peaks represent low values of MIP; Normalized Use Time (NUT), a variable divided into classes as reported in the legend; in the defined intervals the square bracket indicates that the extreme is included, the round bracket that the extreme is excluded. Computer Adequacy (I_{CA}), Results (I~R), Study Pace (I_{SP}), Course Structure (I_{CS}). On the left and top, the observed dendrograms define aggregates of users and sub-indexes, respectively.

to continue the research including in the analysis framework other information, such as the period of fruition; the perceived usefulness to understand the impact of the time learning patterns identified for types and formats of multimedia courses. This analysis will be extended to other instructional methodologies (classroom, game, webinar) because the goal is to give time its proper value for designers, salespeople, and end-users who must have adequate time to learn, i.e, the month of the year in which the course is opened; the characteristics of the target audience; the content, i.e., the thematic area; the connecting device; the perceived usefulness to understand the impact the time learning patterns identified for types and formats of multimedia courses. This analysis will be extended to other instructional methodologies (classroom, game, webinar) because the goal is to give time its proper value for designers, salespeople, and end-users who must have adequate time to learn.

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