The differences in students' perceptions and the traceable usage of learning resources

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Abstract

As online teaching and learning gain more traction, accessibility is becoming increasingly crucial. Learning analytics can be effectively employed to evaluate the accessibility of online courses and track how learners utilize the available resources. With its practical implications, this research delves into how learners use various learning resources and compares their preferences with trace data to assess whether students are using their preferred materials. The study also examines potential differences in learning resource usage among students from different disciplines and age groups. The survey data (n=123) is gathered from two Finnish higher education institutions on two courses. Ultimately, the findings underscore the need for a nuanced approach, as students do not always adhere to their preferences, and there are some variances in learning resource usage among certain disciplines and age groups. Future research on the connection between accessibility, learners' preferences, and learning analytics should expand the data, including the learning outcomes to variables, and examine the longitudinal nature of accessible learning resource usage.

Keywords: e-learning; Learning Analytics; Preferences; Multi-Modal Data; Learning Resources; Finland

Introduction

In recent years, education has undergone a profound transformation toward online education and online courses. The COVID-19 pandemic shifted teaching and learning from face-to-face to online formats worldwide. After the pandemic, students have not returned to physical or hybrid teaching in the same way as might have been expected, at least in fields where physical teaching is not required. Hence, we need more information on how to produce better and more accessible online courses for all students.

However, even before the pandemic, online courses were highly popular; according to Shah (2019), over 120 million learners registered for massive open online courses (MOOCs) in 2019 via platforms such as Coursera, edX and Udacity. This amount had increased to 220 million learners by the end of 2021 (Shah, 2019). The allure of online courses lies in their ability to democratize education, break down geographical barriers, and accommodate diverse learning styles and schedules.

Promoting engagement in online courses is important, as high drop-out rates are known problems within online courses (Aldowah et al., 2020; İrem et al., 2020; Rothkrantz, 2017). Foon Hew et al. (2016) identified five factors that influenced positively keeping the students engaged: 1) problem-centric learning, 2) accessibility and passion of the instructor, 3) active learning, 4) interaction with peers, and 5) usage of online resources. In addition, we see the utilization of various types of resources aimed at enhancing the opportunities for students to complete courses instead of dropping out.

Typically, online courses are completed by going through different resources, often presented in formats such as video, text, audio, or different visualizations. Depending on the course, exercises may range from multiple-choice questionnaires to essays, online discussions, and smaller tasks. Additionally, some courses incorporate peer feedback.

This study focuses on two courses conducted at two Finnish Higher Education Institutions (HEI). The other course was targeted at business students, and the other was a multidisciplinary course. The learning resources were produced in multiple formats – video, text, and audio – for two primary reasons: to enhance the accessibility of the course and, for this study's purposes, to investigate potential differences in how these resources are utilized. As one goal of this study, we aim to initiate discussions on how offering different formats of learning resources can meet the learners' preferences, enhance the accessibility of learning, and provide students with the opportunity to choose the resources that best suit their needs.

Background Literature

The following sections will present the relevant background literature to better understand this study's scope and theme. They following sections are divided to 1) learning analytics in the context of accessibility and learners' preferences, and 2) preferences on learning resources.

Promoting accessibility in learning analytics by understanding the learners' preferences

In recent years, there has been a growing interest in using learning analytics (LA) to assess the accessibility of courses for students with disabilities. After the COVID-19 pandemic, a need for accessibility to online learning emerged (Fonseca et al., 2021). Some good practices exist for designing accessible educational resources (Navarrete and Luján-Mora, 2018), but there is still a need to understand the best practices that could promote accessibility.

Cooper et al. (2012) have suggested that learning analytics (LA) could be used to assess the accessibility of courses. They suggest that LA data can be used to compare the whole body of students with students with disabilities to see if there are parts of the course that result in drop-off. Their study showed that most Open University courses result in a higher drop-out rate for students with disabilities when compared to non-disabled ones. However, there are courses where people with disabilities perform better than the non-disabled with the same measuring. The authors have discussed the factors of module design as possible reasons behind these differences. One might guess that the reason may lie in how accessibility is considered - when a course is arranged accordingly, it is much easier for students with disabilities to perform. Cooper et al. (2012) suggest that these factors should be examined. LA does show where the problem lies but does not explain why it exists. This requires multimodal data to get a more detailed view of the learning design and the perception of learners, which could explain the unknown factors that should be taken care of to offer accessible learning experiences to both learners with and without disabilities.

Disabilities can be divided for example, into visual, hearing, physical, and cognitive disabilities. In the context of learning disability can be seen as a "mismatch between the needs of the learner and the education offered," and accessibility is "the ability of the learning environment to adjust to the needs of all learners" (IMS Global Learning Consortium, 2004). This definition does not highlight the disability itself, but it can apply to all learners. Therefore, learning environments should acknowledge accessibility needs and adapt to the needs of students with disabilities (Cruz et al., 2015) and students without disabilities. Richardson (2009) has connected accessibility with retention and success rates, whereas students acknowledge accessibility as a feature promoting academic achievement (Firat, 2016).

Accessibility has a vital role in the completion rates of courses. Five years of data from STEM (science, technology, engineering, and mathematics) courses arranged in Open University were studied to compare completion rates between students with and without disabilities (Cooper et al., 2016). The average completion rate for students with disabilities was 69.5%, whereas for non-disabled it was 75.3%. With questionnaire data, the students claimed problems of accessibility, including people with dyslexia having problems following videos without subtitles, and some found problems with a lack of printed data or online data. There are differences in completion rates between modules, this suggests there are unknown factors affecting the completion rate (Cooper et al., 2016).

Robust accessibility (the contents work on different types of devices and browsers) has been found to help students even though they are non-disabled. Alexander et al. (2019) have found that easy access can increase the ease of use and willingness to use the learning resources. Still, the concept of accessibility is confusing for some. For example, participants of the study may refer to accessibility as a synonym for the convenience of having all learning resources in one location instead of downloading different resources from different sources (Alexander et al., 2019).

Sometimes, the concept of accessibility is used together with flexibility (MacNeill et al., 2023). Then, it might refer to the possibility of studying without the constraints of time, distance, or competing interests such as work and family (Daniel et al., 2021), access to decent internet connections (Daniel et al., 2021; Schwartzman, 2020), or to resources and activities (MacNeill et al., 2023). Accessibility can set certain hurdles for higher education institutions. Following the accessibility standard limits teacher's possibilities to create new

learning content in a flexible manner, and some learning technologies may not meet accessibility standards (Ableser and Moore, 2018). It is also good practice to let learners choose an option that best suits their needs (Ableser and Moore, 2018).

Mahmoud et al. (2021) conducted a systematic literature review about expectations towards LA and refers to accessibility in the meaning of "data accessibility" which refers to the needs of both faculty (Jones, 2019; Knight et al., 2016) and students (Roberts et al., 2016) to access the data concerning the learning processes data. Here, accessibility is seen as the ability to access data without boundaries (Falcão et al., 2020; Klein et al., 2019). It is important to note that in the learning analytics context, accessibility can also refer to the authority and right to obtain learner data (e.g., Adejo and Connolly, 2017). This is an important question connected with privacy. However, in this study, the focus is not on this type of accessibility.

Different methods are used to examine the learners' perceptions of accessibility. Altinay et al. (2021) interviewed learners with disabilities to map their needs concerning virtual learning environments. They conclude that media, services, and applications should all be designed to be accessible. Lee et al. (2023) have studied the accessibility of LA systems using a questionnaire that focuses on searchability, ease of access, and quick access when necessary. In the context of virtual laboratories, accessibility was examined, and it was found that technological, infrastructural, pedagogical, and cultural barriers must be overcome to enable a better state of accessibility (Deriba et al., 2023).

A recent study by Baek and Aguilar (2023) has studied how LA has been used in relation to students with disabilities. LA is used to predict students with disabilities with difficulties early (e.g., Bogarín et al., 2014; Herodotou et al., 2017, 2019, 2020), to promote the learning process of students with disabilities (e.g., Fadljevic et al., 2020 and Zhang et al., 2020), to explore the accessibility issues students with disabilities face (e.g., Brennan et al., 2019; Verbert et al., 2020), to map the ethics and privacy concerns (e.g., Lang et al., 2018, 2020; Slade et al., 2019), and to use the disability status as a demographic variable in the dataset (e.g., Niaki et al., 2019; Zheng et al., 2019). Their findings suggest that LA has the potential to evaluate and optimise learning designs and support learning experiences.

Baneres et al. (2021) have included accessibility as a requirement in the predictive LA infrastructure designed to provide an early warning system. Morrison et al. (2017) have suggested that AI systems could help learners with disabilities during their learning process. The ethical issue concerning predictive analytics concerns the avoidance of unfairness when predictive analytics may predict disabled learners based on demographic data (Trewin et al., 2019), which might show, e.g., lower passing rates as has been found in the previous studies (Cooper et al., 2016).

Benedetto et al. (2022) have suggested that accessibility could be improved in learning environments by generating multimodal versions of teaching content, multilingual content, and prioritizing the learning resources. Content accessibility and personalization have received little attention, although the number of students with special needs is growing (Benedetto et al., 2022). For example, summarising video lectures effectively improves accessibility (Benedetto et al., 2023).

In summary, LA has been used to assess the accessibility of courses for students with disabilities, and it can potentially evaluate and optimize the learning design and support

learning experiences. The literature suggests that learning environments should acknowledge accessibility needs and adapt to the needs of students with disabilities to promote academic achievement. In this study, we understand accessibility beyond disabilities, we see, for example, that understanding the learners' preferences on course materials and offering different types of materials will make the courses more accessible to all people, and not only for people with disabilities.

Preferences on learning resources

In the context of this study, it's crucial to define the term 'learning resources.' These resources can be external to the learner, such as books or lecture resources, or internal, such as the learner's prior knowledge (Arvaja et al., 2007; Fischer and Mandl, 2005). For this study, we specifically refer to the former as 'learning resources.' These resources function as information repositories (Jeong and Hmelo-Silver, 2010), taking various formats such as text, image, audio, video, animation, and hypertext (Carmona et al., 2007). Combined, these formats form learning resources such as lecture notes, videos, narrated PowerPoint presentations, video transcripts, or audio tracks, which can be described as podcasts.

Cramer et al. (2007) studied how students utilize online resources, such as lecture notes. Their findings were significant, as they revealed that students who perceived resources as helpful performed better on exams. However, the study highlighted a concerning trend: only 20% of the students accessed the available resources. This underscores the importance of resource uptake and its direct correlation with student performance. Kirkwood (2006) further supported this notion in a survey of over 16,000 students, where less than 30% of students reported using online resources at least once a month. Jeong and Hmelo-Silver (2010) echoed these findings, emphasizing that the mere availability of resources is not enough to ensure their use. The pedagogical design of the course must also be considered to support resource uptake.

The preferences of students for different learning resources can vary significantly. Hampton et al. (2017) discovered that students favored videos and narrated PowerPoint presentations as learning methods. These formats were not only perceived as the most engaging but also the most effective for learning. Slater and Davies (2020) identified a preference for external learning resources, such as online lectures, course notes, and primary literature. These resources were seen as accessible, easy to engage with, and directly related to assignments. However, most students largely dislike podcasts and knowledge review quizzes. Jameel et al. (2019) delved deeper into this topic, studying the preferences of medical students and finding distinct differences in learning resource usage between genders. Female students tended to spend more time reading textbooks, while males preferred the lecture handouts provided by their educators. Rahmatullah (2023) has explored female students' preferences between handouts, textbooks, and e-resources from the perspectives of ease of availability, convenient access, easiness to study, how the learning resource helps to understand the concepts, helping to achieve better grades, and the benefit for timesaving. Handouts outperformed other options in almost every aspect. Textbooks were preferred from the point-of-view to clarify concepts, whereas e-resources and handouts were equally preferred considering the convenient access.

Furthermore, students from different age groups seem to prefer different types of studying, including the style of learning and the utilization of learning resources (Morin et al., 2019).

For example, older students (aged 41-70) tend to prefer asynchronous learning, while younger ones (aged 21-30) tend to favor interactive online learning (Simonds and Brock, 2014). This is supported by Hampton et al. (2017), who found that students born between 1946 and 1980 preferred studying asynchronously, while younger students preferred synchronous learning. There is contradictory research whether age affects the resources used in online courses, for instance, according to (Chyung, 2007), older students tended to be more active in discussions. However, some studies have argued that there are no significant differences depending on age in terms of the usage of learning resources and interaction (Ke and Kwak, 2013; Kennan et al., 2018).

To support this study and enhance the accessibility of our courses, we designed the course in an accessible manner. In the other course, accessibility was thought deeply throughout the design process of the course, and in the other course, the materials were offered in multiple formats. In Finland, the promotion of accessible education is based on the Non-discrimination Act (1325/2014) and the Act of the Provision of Digital Services (*Laki digitaalisten palvelujen tarjoamisesta 306/2019, 2019*), we used as a basis guideline which applies to general Web Content Accessibility Guidelines (WCAG) 2.1 (2023).

In this context, accessibility can create opportunities for students to discover new learning preferences or support their existing ones. When materials are provided in multiple formats, such as written and oral, students can choose the method that best suits their learning style, while also making the materials more accessible to people with disabilities.

This research focuses on addressing the following research questions:

RQ1: What are the differences in learning resource usage between the trace data and students' perceptions?

RQ2: What are the differences in using learning resources at different ages?

RQ3: How does previous experience of online studies affect the use of different learning resources?

RQ4: What are the differences in learning resource usage between students from different disciplines?

Materials and Methods

The following sections will present the background information of the collected data and the used methods for analysis.

Participants & dataset

The dataset for this study was gathered from students (n=123) of two online courses organized in two Finnish higher education institutions (HEI). The data includes pre-survey data gathered at the beginning of the courses and the usage data gathered from the learning management system (LMS). This multimodal learning analytics data (Worsley, 2018) is used to contribute positively to accessibility. The data was collected at the beginning of 2024. Students gave their informed consent to participate in the study.

Background information

Descriptive statistics of participating students considering the age of the students are presented in Table 1, and the students' preferences on the different forms of learning resources are presented in Figure 1 divided by the age of the students. The preferences on different learning resources changes between different age groups. The majority of students belonged to age group 25-34 years old, followed by 18-24 years old. Table 2 presents the division of the students between different disciplines, most were studying business, followed by technology students.

HEI	Age	Counts	% of Total
HEI1	18-24	17	13.8 %
	25-34	25	20.3 %
	35-44	19	15.4 %
	45-64	4	3.3 %
HEI2	18-24	29	23.6 %
	25-34	25	20.3 %
	35-44	3	2.4 %
	45-64	1	0.8 %

TABLE 1: Participating students within courses
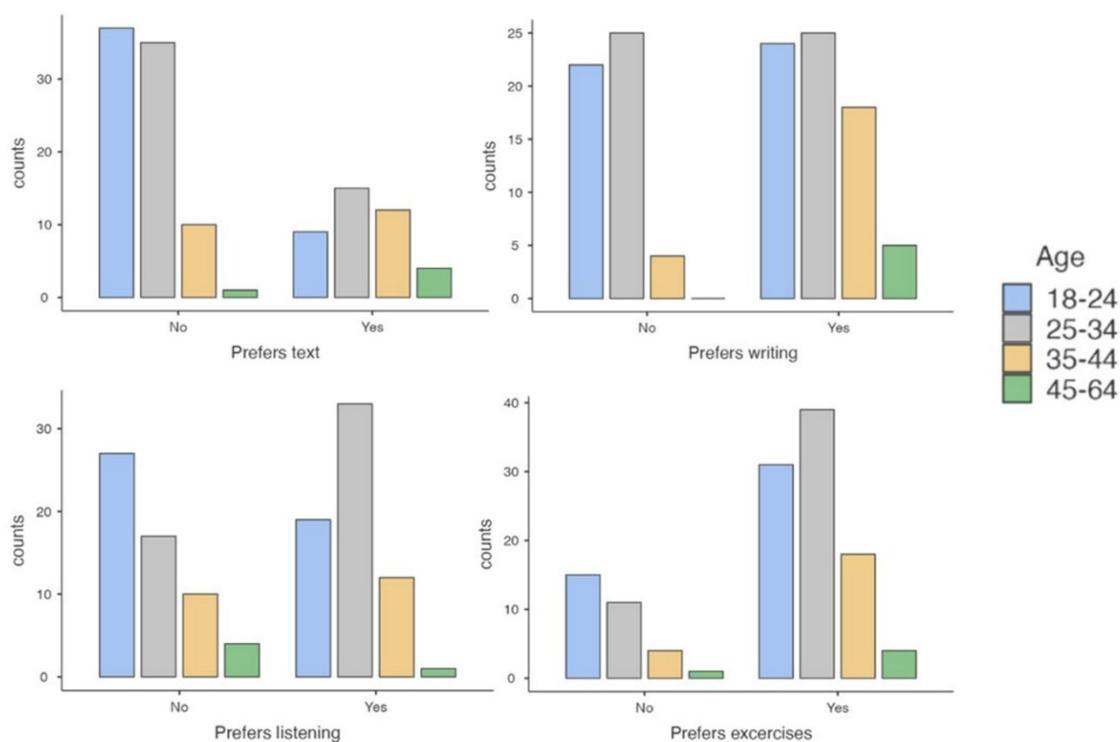
Figure 1: Students' learning preferences

Discipline	N	% of total
Business	74	60.2
Communication	8	16.3
Technology	20	11.4
Humanities and social sciences	14	6.5
Administrative sciences	5	4.1
N/A	2	1.6

TABLE 2: Students' discipline

In the presurvey, students were asked for information concerning their background. The questionnaire is included as an appendix. The age, discipline of study, and the number of online courses they had completed before joining this course were asked. Furthermore, students responded to questions about their preferences for learning resource usage, asking if they would prefer using visual, text, or audio resources while studying. For this question, a student could choose one or more types of preferred learning resources. The preferences were asked to identify the types of learning resources that would best fit their needs and help them learn (Ableser and Moore, 2018).

The usage data of the students were gathered from the learning management system (LMS). For privacy and security reasons, another HEI did not allow the use of log files to trace the usage of the learning resources using log files, which is the standard procedure in LA. Therefore, we decided to use the user report showing the number of times a student has used different learning resources. We collected the data of each student from the first half of the course, considering how many times a student has used each learning resource available. For every lesson, the learning resources were available for the students in different forms (video, transcript, audio, and audio) with identical content in every form. The course teachers crafted the learning resources into different forms to enhance the accessibility of the course resources and to enable the data gathering for this study. On some videos the lecturer were visible in the video, whereas on some video resources only the content were presented. We coded the data according to the running order of the lessons/topics (lesson 1, lesson 2, etc.) and each learning resource, with the code representing the form of the learning resource (video, transcript, audio, handout). When combined, each learning resource was identified with details of both the lesson and the form of the learning resource (e.g., "lesson 1 video" or "lesson 3 transcript"). As a result, the data included the number of times learning resources for different lessons were used for each student.

Methods

By utilizing the usage statistics, we could aggregate a value representing the usage proportion for each learning resource. This data is crucial in answering RQ1, as it allows us to compare these statistics with students' pre-survey answers about their preferred learning resources, thereby providing valuable insights into their resource preferences. The study aims to determine if there is a relation between students' reported preference for the learning

resources and the logged usage of the learning resources. Prior to conducting the analysis, the assumptions of independent samples t-test, which are normality and homogeneity of variance, were examined using Shapiro-Wilk statistics and Levene's test. The result of Shapiro-Wilk test showed that the assumption of normality was violated. However, the Mann-Whitney U test, a robust alternative to the independent samples t-test, was used to ensure the validity of our analysis.

To answer RQ2, we categorized the students based on the age groups used in the presurvey (18-24, 25-34, 35-44, 45-64). For the oldest students, we combined two categories of the survey. This decision was made to protect the anonymity of the only respondent in the 55-64 age category. This approach, while explorative, was chosen to help us analyze the results descriptively and illustrate the potential differences between students of different ages, thereby aiding in formulating hypotheses for future studies on the same topic. To check if there are significant differences between age groups, we performed a Kruskal-Wallis test.

Students' experiences from their previous online courses could influence their use of learning resources. To investigate this aspect and answer RQ3, we categorized the respondents into four groups based on the number of online courses (no courses, 1-5 courses, 6-10 courses, over ten courses) they had completed before joining the course from which the data was collected. This descriptive approach was chosen to examine the possible differences, thereby providing insights into the impact of previous online course experiences on learning resource usage. We performed a Kruskal-Wallis test to check the statistical significance between previous experience on online courses and different types of learning materials used.

Finally, to answer RQ4, we categorized the students based on the disciplines (Business, Communication, Technology, Humanities and Social Sciences, and Administrative Sciences) to determine the differences in learning resource usage among students from different disciplines. Two respondents did not respond to the question concerning the discipline. Similarly, with the previous RQs, we performed a Kruskal Wallis test.

Results

RQ1: Differences between self-reported preferences and the logged behavior

According to the Mann-Whitney U test, no significant differences existed between students who favored the learning resources in question and those who did not. Table 3 displays the statistics for each preferred material type and the usage of the different materials. The students are categorized into two groups based on their material preferences. For instance, 40 students prefer text, whereas 83 students do not. The most prominent variance in mean usage is evident among visual learners and their use of video resources. Students who prefer visual learning have a mean usage of 0.81, whereas those who do not prefer this type of material have a mean of 0.54. However, the p-value for this difference is 1.000.

TEXT	Preferred learning resource N=40			Unpreferred learning resource N=83			Mann-Whitney	Effect size
	Mean	Median	St.d.	Mean	Median	St.d.	p	r
video	0.70	0.93	0.356	0.76	1.00	0.372	.157	.10
transcript	0.24	0.09	0.312	0.17	0.00	0.298	.968	.19
handout	0.23	0.13	0.274	0.21	0.00	0.326	.875	.12
audio	0.00	0.00	0.014	0.00	0.00	0.016	.897	.04

VISUAL	Preferred learning resource N=91			Unpreferred learning resource N=32			Mann-Whitney	Effect size
	Mean	Median	St.d.	Mean	Median	St.d.	p	r
video	0.81	1.00	0.318	0.54	0.57	0.424	1.000	.36
transcript	0.17	0.00	0.279	0.27	0.13	0.357	.054	.18
handout	0.20	0.00	0.298	0.27	0.13	0.338	.183	.10
audio	0.00	0.00	0.018	0.00	0.00	0.000	.852	.03

LISTEN	Preferred learning resource N=65			Unpreferred learning resource N=58			Mann-Whitney	Effect size
	Mean	Median	St.d.	Mean	Median	St.d.	p	r
video	0.71	1.00	0.372	0.78	1.00	0.360	.063	.14
transcript	0.20	0.00	0.318	0.18	0.00	0.288	.500	.00
handout	0.23	0.13	0.308	0.21	0.00	0.313	.721	.06
audio	0.00	0.00	0.019	0.00	0.00	0.008	.692	.01

TABLE 3: A comparison between students who prefer and do not prefer the type of learning resources in question. Each row represents the form of learning resources and values on the line represent the percentage of corresponding learning resource usage.

RQ2: Using learning resources at different ages

When comparing how students use different learning resources at different ages, we can mostly see similarities between the age groups (Figure 2). For example, using audio resources was rare at all age groups. Hence, the figure is not directly comparable to other types of materials due to the different scales on the y-axis. Using video resources on the other hand, was highly popular in all age groups. According to the Kruskal-Wallis test, the only significant difference between age groups is in video percentage, χ^2 (3) = 11.50, p = .009, ϵ^2 = .09. The older students (age 35 and above) tend to rely on the videos even more than the younger students (from 18 to 34). Using handouts and transcripts was rarer in the age group of 45-54 years olds compared to other age groups. Interestingly, the oldest students (45-64) hardly use transcripts, handouts, or videos.
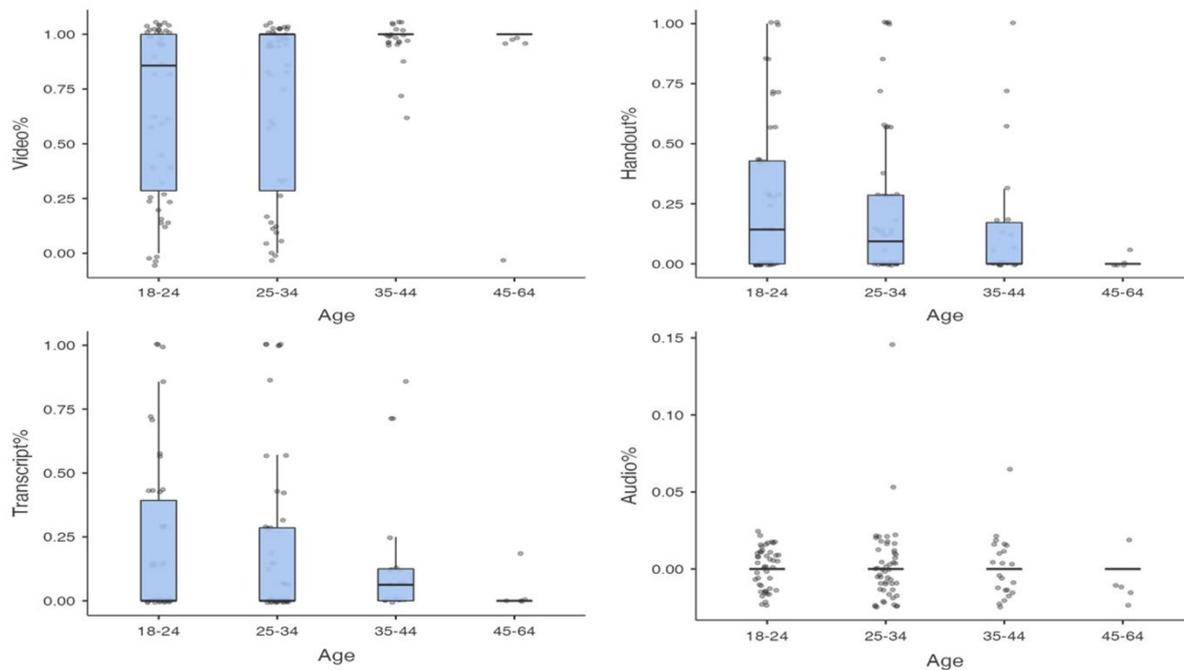
Figure 2: Descriptive usage statistics of different types of learning resources for students of different age groups.

RQ3: The role of previous experience for the use of learning resources

When comparing how students with varying levels of experience in online learning utilize learning resources, we can identify differences (Figure 3). According to a Kruskal-Wallis test, there is a significant difference in percentages on video, χ^2 (3) = 11.06, p = .009, ϵ^2 = .10, transcripts χ^2 (3) = 12.01, p = .007, ϵ^2 = .10, and handouts χ^2 (3) = 11.11, p = .011, ϵ^2 = .10. The group of students who have not previously completed any online courses (leftmost in Figure 3) tend to favor video resources, with only three outliers in this group having watched a quarter of the video resources. Videos are the most used resource for the remaining students in this group. Some students in this group use handouts or transcripts in addition to videos, but audio resources are not utilized. The low usage rate of audio files is consistent across other groups. As the number of previously completed courses increases, utilization becomes more diverse. Students who have completed one to five online courses rely less on video resources than those with no prior online course experience. Along with video resources, students in this group use more transcripts and handouts. In the third group (six to ten previously completed online courses), the usage of different learning resources is more evenly balanced. Video resources are still the most utilized, but not as overwhelmingly as other resources. The proportions of handouts and transcripts are higher for this group of students. In the last group of students (over ten completed online courses), the usage of video resources increases once again, while handouts and transcripts are less frequently used. A few outliers in this group have utilized all or almost all handouts or transcripts.
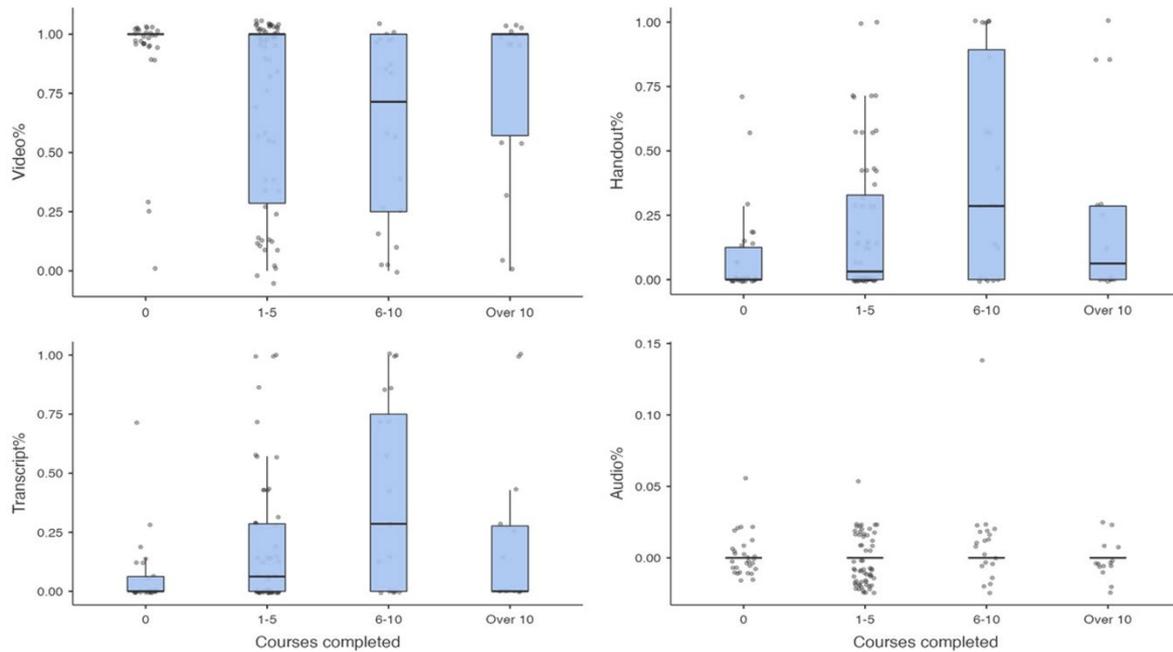
Figure 3: Descriptive usage statistics of different types of learning resources for students with different numbers of completed online courses.

RQ4: Differences in the usage of learning resources between different disciplines

When comparing the usage of learning resources between different disciplines, we can see some clear differences (Figure 4). According to a Kruskal-Wallis test, there is a significant difference in percentages on video, χ^2 (5) = 64.28, p = <.001, ϵ^2 = .53, transcripts χ^2 (5) = 32.44, p = <.001, ϵ^2 = .27, and handouts χ^2 (5) = 37.36, p = <.001, ϵ^2 = .31. For example, business students seemed to favor videos clearly over other types of resources. They also used fewer transcripts and handouts compared to other disciplines. In all disciplines, the use of audio resources was rare. Within technology and administrative sciences, the usage of videos was somewhat more common than other types of resources. However, other types of resources were also used evenly. The communication and humanities and social sciences students seemed to favor using handouts and transcripts over other resources compared to other disciplines, however, the differences were relatively small.
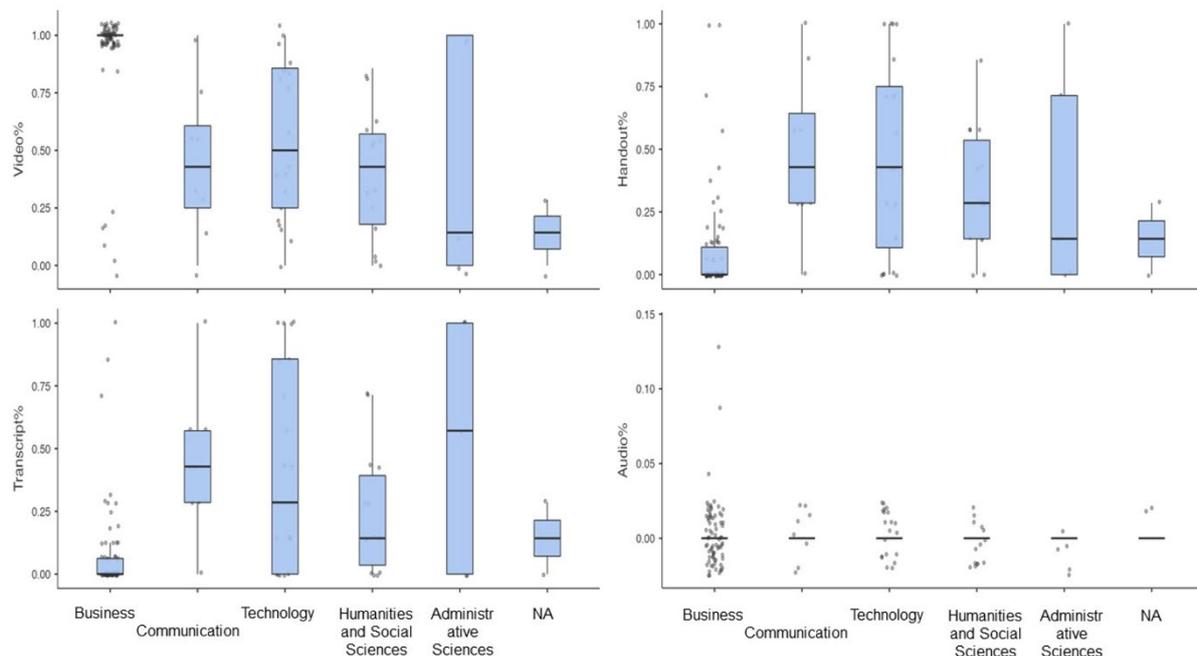
Figure 4: Descriptive usage statistics of different types of learning resources for students from different disciplines.

Discussion

It is a good practice to let learners choose an option that best suits their needs (Ableser and Moore, 2018). According to the results, it is difficult to say what would be the best option for students. There were no significant differences between the different types of material usage that could have been connected to the students' preference for learning resources. This suggests that students do not use the materials they say would be the best option for them.

However, the availability of subtitled video materials offers a unique advantage. It caters to the preferences of three different types of learners. The video component appeals to visual learners, while the audio track benefits auditory learners. The subtitles allow reading comprehension, making it a versatile resource for learning in various settings (Gernsbacher, 2015). This underscores the potential of well-prepared videos as an accessible learning resource, potentially eliminating the need for additional materials for students with specific accessibility needs. However, it is important to note students using screen reader, who are customed to higher listening speed (Asakawa et al., 2003; Miyashita et al., 2007) for example, by allowing options to speed up the video. Also, the role of the presenter (Fiorella et al., 2019) should be considered and studied furthered to check how it affects the usage of learning resources.

The results can be a consequence of response bias. Students might self-report behavior that they do not actually perform. Perhaps they give an answer they think is the "correct" one (e.g., Krumpal, 2011; Lavidas et al., 2022; Meisters et al., 2020) or they just don't put enough

effort into responding. The response bias can result from a lack of self-regulation – a student knows how they could learn the best but cannot perform the actions needed to achieve their learning goals. This underscores the importance of providing assistance to students, empowering them to perform better in online courses (Heikkinen et al., 2023).

Likewise, it is possible that students are accustomed to using certain types of resources since they are most commonly available. For example, videos are common in online courses; hence, students expect that they will use videos in this course as well. However, they try out transcripts for the first time and find out that it is a better way for them to learn compared to watching videos. The high usage rates of video materials align with the previous findings that highlight the engagement and effectiveness factors of video resources (Hampton et al., 2017).

From the insights gleaned in Figure 3, it becomes evident that students new to online courses tend to rely heavily on video resources. This could suggest that this format is particularly user-friendly and straightforward. It is also possible that students are nowadays more accustomed to consuming videos than other types of media, which makes videos easier to grab onto. However, it may not necessarily be the most effective option for long-term learning. On the other hand, students with more experience in online learning demonstrate remarkable adaptability, utilizing a broader range of resources. This showcases their ability to understand and utilize what works best for them, a skill that can be honed through online learning. This adaptability should serve as a source of inspiration for educators and designers, encouraging them to provide various resources that cater to the diverse learning needs of their students. As it is stated by Jeong and Hmelo-Silver (2010), the availability of resources is not enough. The learning design of the course must be considered as well.

The results indicate differences in how students use learning resources based on age or discipline. Previous studies (Ke and Kwak, 2013; Kennan et al., 2018) have found that there are no significant differences depending on the age of learners when it comes to the usage of learning resources. Interestingly, in this study, the oldest students were the ones who were the most reliant on video materials. In contrast, younger students, belonging to generation Z (Shorey et al., 2021), had higher probability to try out other forms of resources. It is notable that business students tend to rely more on video resources than students in other disciplines, which is in line with previous findings (Arbaugh et al., 2009). According to the authors' own perceptions, this could be because business students are more accustomed to watching videos, whereas technical students might prefer reading texts. Another possibility is that the differences stem from how the courses are structured. For example, the other course of this study was targeted at business students, while another was more multidisciplinary. In such cases, the appeal of videos could vary, leading to differences in usage patterns. The discipline or the age does not have any role in the amount of using audio resources. Podcasts have been found to be an unpopular form of resource (Slater & Davis 2020), and this study verifies this finding.

Limitations

This study has been focusing on two courses in two Finnish HEIs. The study has gathered the data from the beginning of the courses. Thus, the results of this study are not generasible. The number of courses should be increased to determine if the identified issues

are found in different courses. It is well known fact that some students tend to procrastinate on courses. Therefore, the beginning of the course does not necessarily show the true nature of the studying process. For this reason, the data collection should cover the entire course to see if there are temporal changes in the students' behavior during the course.

The difference in the usage of learning resources might indicate that there are differences in learning design, which might affect how students use the learning resources. This issue is beyond this study's scope, but the learning design's impact and how it affects the usage of learning resources should be studied further.

In addition, this study is limited by its survey format, which does not afford respondents the opportunity to elaborate on their answers or researchers the chance to pose additional questions. For instance, it's possible that students have previously only completed synchronous online courses and this asynchronous online course is their first experience with such a format. Alternatively, students may have only taken courses within their own disciplines and are accustomed to the resources typically offered within those contexts. In addition, since we did not collect the background data (e.g, disability information) from students, we cannot identify if people with disabilities would use the learning resources differently compared to people without disabilities. However, we can say that there is a need for different types of materials, to make the courses more accessible for all students.

Lastly, the response bias might be affecting the students' responses. Thus, they might report different preferences than they would actually perform. The impact of the response bias should be investigated to determine how it affects the responses. Understanding and controlling for biases is crucial for the validity of learning analytics research.

Future work

This study includes the first steps to improving accessibility with the help of learning analytics. Several approaches could be used to take the following steps on this journey. First, the dataset could be expanded by including the data from a full course. If the data of a complete course were combined with the grades students achieve from the course; it could be possible to investigate further if the students who manage to use their preferred learning resource can achieve better learning outcomes. Another perspective could be focusing on the self-reported accessibility needs. Combining this data with LA data would enable a more detailed understanding of how the learning environment serves the needs of students with accessibility needs. Third, the preferences in this study were investigated in isolation. The results show that students do not prefer only one type of learning resource, but instead, there are overlapping preferences. Thus, clustering might be used to create learning profiles based on the students' preferences. Then, these profiles could shed more light on learning resource usage and how they affect learning outcomes. Finally, the learning resource usage depends on the number of courses a student has completed. This suggests that understanding the most suitable learning resources improves with the experience of online learning. It would be interesting to see how this development happens. For this need, a longitudinal approach might be suitable.

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Appendix

Questionnaire

- Age (choose one)
  - 18-24
  - 25-34
  - 35-44

- - 45-54
  - 55-64
  - 65 or over
- What field are you studying? (text box)
- How many online courses you have completed before? (choose one)
  - I haven't
  - 1-5
  - 6-10
  - Over 10
- When I am studying, I learn best when I… (choose one or multiple):
  - Look at the visual materials (e.g., pictures, graphs, charts, videos)
  - Read textual materials
  - Listen to the materials (lecture, recording)
  - Write notes
  - Complete exercises