Data-driven Decisions of Higher Education Instructors in an Era of a Global Pandemic

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Abstract
The impact of the COVID-19 pandemic on the higher education sector has been overwhelming, with emergency responses that have affected decision-making processes. Yet, our understanding of higher education instructors' perspectives regarding the process of data-driven decisions, especially in times of emergency, is still limited. We aimed at characterizing the types of data-driven decisions that higher education instructors have made in their courses. This was done while asking the instructors to reflect upon a face-to-face (F2F) course that was suddenly shifted to emergency remote teaching (ERT), due to the COVID-19 pandemic outbreak. Taking a qualitative approach, data were collected via an open-ended online questionnaire distributed among 109 higher education instructors from different countries. The findings suggest that the instructors mentioned a wider range of data sources, and a wider range of data-driven decisions while referring to the ERT mode, compared with their F2F instruction. In F2F teaching, the instructors mostly provided students with real-time educational assistance. In ERT, the instructors mostly adjusted the course requirements, promoted collaboration among students, and offered them social and emotional support.

Keywords: data-driven decisions, educational data, online teaching, higher education, instructor perspective

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Data-driven decision-making is the process by which instructors collect and analyze data to guide and support educational decisions (Michaeli et al., 2020; Prinsloo & Slade, 2014). In higher education face-to-face (F2F) courses, instructors are accustomed to observe educational data and respond to it, while relying on both verbal and non-verbal communication (Herodotou et al., 2019; Vanlommel et al., 2017). However, during the transition to remote teaching, as occurred during the COVID-19 outbreak, the way instructors and students interact has significantly changed, and as a result, so has the range of data to which instructors are exposed (Usher, Hershkovitz & Forkosh-Baruch, 2021). While teaching remotely, higher education instructors experience indirect interaction with students, hence they are less exposed to non-verbal data that is continuously available in the physical classroom (Barak & Usher, 2020; Barak & Usher, 2022; Herodotou et al., 2019; Kumar & Johnson, 2019). This creates a situation where some of the students' behavior and actions are harder to track (Gašević et al., 2016; Picciano, 2012), which might compromise the data-driven instructional process (Gašević et al., 2016).

Still, online environments may assist in the teaching process when applying data-driven decision-making; the instructors can benefit from access to the varied data about learners that is gathered automatically via learning analytics (LA) systems (Cerro Martínez et al., 2020; Shibani et al., 2020; Tsai et al., 2019). Studies have highlighted the role of LA systems as a means to help instructors gain actionable insights into students' learning behaviors, to support educational decisions (Fynn, 2016; Larrabee Sønderlund et al., 2019; Prinsloo & Slade, 2014).

However, mere access to educational data is not enough. It has become clear that LA systems should be made accessible to educational stakeholders in a way that is easy to understand and to act upon (Datnow & Hubbard, 2016; Michaeli et al., 2020; Usher & Hershkovitz, 2022). For instructors to embrace the data-driven instructional process there is a need to implement bottom-up approaches that include the instructors as the main stakeholders, rather than the end-users (McKee, 2017; Ndukwe & Daniel, 2020). Yet, our understanding of instructors' viewpoints regarding the process of data-driven decisions, especially with regard to remote teaching in times of emergencies, is still limited (Ndukwe & Daniel, 2020; Usher, Barak, & Haick, 2021). We aim at bridging this gap by exploring variations in instructors' perceptions of the use of educational data for decision-making in the COVID-19 era, compared with the pre-pandemic period.

Literature Review

Data-driven decisions in higher education

Higher education instructors constantly rely on a variety of learner data to gain a deeper understanding of their class and individual students, to provide learners with meaningful feedback, and to reflect upon their own teaching (Harindranathan & Folkestad, 2019; Leitner et al., 2017; Picciano, 2012). This is known as the process of data-driven decision-making. Data-driven decision-making refers to collecting, understanding, and analyzing educational data to guide and support educational decisions (Prinsloo & Slade, 2014). Such educational data address the academic, behavioral, and socio-emotional aspects of the learning process, and are collected in a variety of ways, from academic assignments, through monitoring classroom participation, to observing students' non-verbal communication during sessions (Vanlommel et al., 2017). Based on educational data, instructors constantly make decisions, such as which content to focus on, how to best engage the students, and which students should receive targeted support (Harindranathan & Folkestad, 2019; Prinsloo & Slade, 2014; Vanlommel et al., 2017).

In many cases, such decisions are taken based on the instructor's experience and understanding of the situation, and not necessarily on empirical evidence (Michaeli et al., 2020; Vanlommel et al., 2017). This is often the case in face-to-face (F2F) teaching, where instructors are accustomed to observe educational data and respond to it (Herodotou et al., 2019; Vanlommel et al., 2017). However, while teaching online, instructors experience indirect interaction with students and they are less exposed to non-verbal data that is continuously available in the physical classroom (Herodotou et al., 2019; Kumar & Johnson, 2019; Usher & Barak, 2020). This creates a situation in which many of the learners' actions (e.g., navigating through the course pages or multiple attempts to solve a problem) might be harder to track (Gašević et al., 2016; Harindranathan & Folkestad, 2019; Picciano, 2012).

Still, while teaching online the instructors can benefit from access to various data sources including students' interactions with a given tool, contributions to a discussion forum or chat, survey responses, students' performance, demographic data, course content, and so on (Vieira et al., 2018). Such data is gathered automatically and continuously via online learning systems (Cerro Martínez et al., 2020; Tsai et al., 2019), and analyzing it can support and guide instructors' decision-making (Archer & Barnes, 2017; Gašević et al., 2016; Gutiérrez et al., 2020). Instructors may decide to make pedagogic changes in real-time, including modification of the existing instructional design to encourage productive learning behaviors (Harindranathan & Folkestad, 2019; McKee, 2017).

But the exponential growth of data provided by online learning systems can be a bit overwhelming. Instructors need to rapidly capture the ever-increasing amount of information about students' learning, interpret this diverse body of information in the light of students' progress, evaluate it in light of curricular goals, and make informed decisions about the next learning steps (Cerro Martínez et al., 2020; Vatrapu et al., 2011). Instructors typically have a difficult time processing and interpreting such a large and diverse amount of data, as they have a limited understanding of necessary data mining and processing techniques (Vatrapu et al., 2011; Vieira et al., 2018) or due to a delay in accessing critical information (Cerro Martínez et al., 2020). This is where learning analytics come into play (Larrabee Sønderlund et al., 2019; Siemens, 2013; Tsai et al., 2019; Vieira et al., 2018).

Learning analytics (LA) refers to the measurement, collection, analysis, and reporting of data about learners and their contexts (Vieira et al., 2018). LA tools have emerged as a technology to enable instructors to engage with educational data effectively and provide insights into students' learning processes (Archer & Barnes, 2017; Harindranathan & Folkestad, 2019; Michaeli et al., 2020; Vieira et al., 2018). In the last two decades, the LA field has captured more attention from higher education researchers worldwide (Larrabee Sønderlund et al., 2019). The bulk of empirical studies about LA in higher education have focused on using analytics systems for the prediction of student performance and drop-out and retention (Hilliger et al., 2020; Ifenthaler & Yau, 2020; Nyland, Croft, & Jung, 2021). However, what is less prominent is the voice of the instructors, who are important stakeholders in the process of adopting and implementing innovative learning technologies (McKee, 2017; Usher & Hershkovitz, 2022). We have little insight into their perspectives regarding the use of educational data to support decision-making processes (Gutiérrez et al., 2020; Guzmán-Valenzuela et al., 2021; Hilliger et al., 2020; Ndukwe & Daniel, 2020; Nyland, Croft, & Jung, 2021).

Instructors' perspectives about data-driven decisions

Successful use of educational data to inform decisions highly depends on the acceptance of the instructors (Rienties et al., 2018; Siemens, 2013). Understanding instructors' perspectives regarding the use of educational data is critical since they are the ones who access and interpret the data, draw conclusions, and make informed decisions (Guzmán-Valenzuela et al., 2021; Leitner et al., 2017). Indeed, recent publications have identified instructors' needs regarding the implementation of LA (McKee, 2017; Usher & Hershkovitz, 2022) and developed new strategies for co-designing such tools with instructors (Holstein et al., 2019). Several studies have reported that instructors often use the information generated by LA systems to identify students who are struggling or falling behind, and "reach out" by contacting them personally, usually via emails (McKee, 2017; Nyland et al., 2021; Usher & Hershkovitz, 2022).

Another line of research has reported on several major challenges faced by higher education instructors while trying to implement learning analytic systems in their classes (Usher & Hershkovitz, 2022; Vieira et al., 2018). To effectively use learners' data, instructors should develop the knowledge and skills to analyze and use data to improve instruction (Datnow & Hubbard, 2016). Yet, instructors often lack adequate data literacy skills (Hilliger et al., 2020). Instructor data literacy refers to the ability to effectively engage with data and analytics to make better pedagogical decisions (Datnow & Hubbard, 2016; Ndukwe & Daniel, 2020). The lack of such an ability might result in the poor interpretation of analytics, which in turn can lead to uneducated decisions that might harm students and create more inequalities in access to learning opportunities (Ndukwe & Daniel, 2020). Moreover, instructors reported having overwhelmingly large amounts of data from different sources, and a lack of personalized, accurate, and timely information (Hilliger et al., 2020; Ifenthaler & Yau, 2020; Rienties et al., 2018). It seems that although instructors are expected to make rapid decisions in a dynamically changing environment, they often do not get the information they need for decision-making in real-time and in an 'actionable' format (Usher & Hershkovitz, 2022; Vatrapu et al., 2011). This is problematic, especially since accurate and timely data were documented as necessary to help instructors make informed decisions regarding their teaching (Archer & Barnes, 2017; Fynn, 2016).

Most of the above-mentioned publications have focused on the perspectives of instructors who teach in face-to-face courses that use online learning management systems (Shibani et al., 2020), in hybrid courses, or massive open online courses (Ifenthaler & Yau, 2020). There is a lack of studies that explore variations in instructors' perceptions regarding the use of educational data for decision-making in their face-to-face instruction, compared with their remote teaching. It is important to understand the way new learning contexts influence instructors' intentions and how they approach their teaching (Jensen, Price, & Roxå, 2020). This is specifically critical in the current shift from face-to-face to emergency remote instruction that has become the prevalent form of learning at many universities worldwide due to the outbreak of the COVID-19 pandemic (Ezra et al., 2021; Marasi, Jones, & Parker, 2020; Ndzinisaaand & Dlamini, 2022).

Emergency remote teaching

Teaching in times of emergency differs from carefully planned learning experiences that are initially designed to be delivered online (Barrot et al., 2021; Hodges et al., 2020). The concept of emergency remote teaching (ERT) refers to a temporary pedagogical shift to an alternate teaching mode as a result of unique circumstances, such as the spread of the COVID-19 pandemic worldwide (Hodges et al., 2020). The impact of COVID-19 on higher education worldwide has been overwhelming with a quick and unexpected shift from face-to-face to remote teaching (Marasi et al., 2020; Usher et al., 2021b; Walsh et al., 2021).

Traditionally, instructors who deliver online courses begin planning them several months in advance, receiving formal training and support from expert university staff (Walsh et al., 2021). Converting an academic course from in-class instruction to an online format requires time and effort (Hodges et al., 2020). With the sudden transition to ERT, instructors were expected to make significant changes to their courses and instruction without a reasonable level of technical and digital pedagogical support (Ndzinisa & R. Dlamini, 2022). The importance of providing online instructors with formal training and institutional support is highlighted by the results of two recent surveys that explored responses of faculty across the United States regarding the transition to ERT during the COVID-19 outbreak (Marasi et al., 2020; Walsh et al., 2021). The results indicated that faculty who received formal training in online education had a more positive ERT experience, while faculty who never received training struggled more (Walsh et al., 2021).

Providing students with proper support in times of emergencies is critical as well. Prior studies have mentioned that the unique circumstances of ERT could aggravate the already known challenges experienced by online learners, such as lack of tutor assistance and an impaired sense of community and connectedness (Ezra et al., 2021; Walsh et al., 2021). Indeed, the survey mentioned earlier demonstrated that some faculty members found themselves making deeper, and more personal connections with their students during the ERT, helping them with technological, mental, social, and health issues. This insight was also demonstrated in a study that explored the way university instructors perceive the differences between teaching F2F and online. The participating instructors reported a shift in student-teacher interaction towards more frequent one-on-one communication with their online students (Jensen, Price, & Roxå, 2020). Understanding the challenges and unique characteristics of ERT allows ongoing improvements in course design and practice as well as better decision-making about how to maintain high teaching and learning standards (Hodges et al., 2020).

In the new educational climate brought on by the COVID-19 pandemic, it is of particular importance to understand the way instructors use and act upon educational data, both in emergencies and in routine. This is based on the understanding that this period of crisis will have long-term consequences for how the higher education environment of the upcoming years will be shaped. Based on this perception, a recent publication took a quantitative approach to explore the types of educational data that drive higher education instructors to make decisions, in F2F versus ERT modes (Usher et al., 2021b). The results indicated that the instructors reported a higher intention towards making data-driven decisions in ERT, compared with F2F instruction. Moreover, while referring to the ERT mode, the instructors mostly relied on educational data about students' collaborative learning and social and emotional state. Yet, we still lack an understanding of the actual decisions made by instructors based on such educational data.

Considering this, the goal of the current study was to characterize the types of data-driven decisions that higher education instructors have made in their courses. This was done while asking the instructors to reflect upon a face-to-face (F2F) course that was shifted to emergency remote teaching (ERT), due to the COVID-19 outbreak. To meet this goal, the following research question was explored: What characterizes the types of data-driven decisions that instructors have made in F2F vs. ERT modes?

Methods

Research participants

Our participants included 109 higher education instructors, who shifted from teaching F2F to teaching online, due to the outbreak of COVID-19. Participants included 52% males and 48% females, with an average teaching experience in higher education of about 15 years. The distribution of respondents by continent included Asia (39%), North and South America (29%), Europe (22%), and Africa (10%). The distribution of respondents by faculty included Natural Sciences (36%), Humanities (29%), Social Sciences (20%), and Applied Sciences (15%). Participants were recruited using snowball sampling, starting with the authors' professional and personal networks.

To ensure the research is conducted ethically, all participants were asked to sign an informed consent form, detailing the research goal, process, and participants' rights. The participants were informed that participation is voluntary, and they were given the choice to withdraw at any time. Participants were not offered an external incentive for taking part in this study. The study was approved by Tel Aviv University's Ethics Committee.

Research methods and tools

This study applied a qualitative phenomenological research design, in which the researchers describe the lived experiences of individuals about a phenomenon as described by participants (Creswell, 2014). Using the lens of the instructors' perspective, we took a within-subject approach, where participants self-reported their perceptions in the context of a single course and regarding its two modes of teaching. Data were collected in March-June 2020 via an online questionnaire that included both closed-ended and open-ended questions. In the closed-ended questions, which were the basis for our prior study, the instructors were asked to rate their willingness to make data-driven decisions in F2F teaching and ERT. In the two open-ended questions, which were the basis for this study, the instructors were asked to elaborate on the types of data-driven decisions they would like to make, or have made, in the two settings of the course, that is, F2F and ERT. Hence, the following two questions were presented to the participants: "Could you elaborate on the kinds of decisions or actions you would take based on learners' data in the F2F mode of the course?" and "Could you elaborate on the kinds of decisions or actions you would take based on learners' data in the ERT mode of the course?"

Data analysis

The qualitative data from the questionnaire were analyzed using the directed approach to content analysis, in which the researchers use codes that are derived from an existing theory or relevant research findings (Hsieh & Shannon, 2005). When answering the first closed-ended part of the questionnaire, instructors were asked to rate their level of interest in the following seven dimensions of educational data: course resources, collaborative learning, instructor-led discourse, assignment feedback, self-reflection, social and emotional support, and independent learning. These dimensions were adapted from Picciano's integrated model (Picciano, 2017), in which seven dimensions regarding the pedagogical aspects of online education are portrayed. Hence, while analyzing instructors' responses to the open-ended part of the questionnaire, it seemed appropriate that the seven dimensions of educational data from Picciano's model will serve as the seven codes for analysis (see Table 1).

Table 1
The Seven Dimensions of Educational Data Based on Picciano's Integrated Model

	Dimension of educational data	Explanation
1	Course resources	The course content that is uploaded online, such as PPTs and reading material.
2	Collaborative learning	The collaborative activities presented in the course, such as group problem-solving and wikis.
3	Instructor-led discourse	The discussions that the instructor holds during lessons.
4	Assignment feedback	The feedback and evaluation of the course's assignments that students receive from the instructor.
5	Self-reflection	Self-reflection on their own learning process during and after the class.
6	Social and emotional support	The social and emotional support students receive from their peers and the instructor.
7	Independent learning	Self-studying outside the classroom and without direct supervision.

The authors read the transcripts and highlighted all text that on first impression appears to represent one of the seven dimensions and coded all highlighted passages using the predetermined codes. After the coding process, the authors again reviewed the transcripts according to the conventional (inductive) data analysis approach, in which the researchers immerse themselves in the data independently to allow new insights to emerge. In the next step, the two authors compared emergent themes to ensure inter-coder reliability, until full agreement was reached (Creswell, 2014). As a result of this comparative exercise, a few themes were merged to avoid overlaps.

Results

Characterizing types of data-driven decisions, F2F vs. ERT

The analysis has raised four themes for the types of data-driven decisions. Each theme was linked to one of the seven dimensions of educational data that were detailed in Table 1.

Providing real-time educational assistance—F2F and ERT

The first type of data-driven decision that was repeatedly mentioned by the instructors was contacting students in real time to suggest guidance and assistance with the course content and assignments. This theme was linked to the "course resources" dimension of educational data. The main sources from which the instructors collected data to support this decision were students' participation patterns (F2F) and students' grades in quizzes and assignments (ERT). This decision was apparent with reference to both the F2F and the ERT modes; it was mentioned in 25% of the responses that referred to the F2F mode and 18% of the responses that referred to the ERT mode.

While referring to the F2F mode, the main source from which the instructors collected educational data was students' participation patterns during the lectures. The main purpose of providing students with real-time educational support was to help low-performing students to successfully complete the course:

If I had a feeling that a student was having difficulties understanding the material discussed in class [...] If I noticed that a certain student did not participate or did not take part in the class activities, I approached that student after class and tried my best to explain the problematic concepts. I did my best to help each student complete the course successfully. (I6, Male)

Conversely, while referring to ERT, the main source from which instructors collected educational data was students' grades in quizzes and assignments retrieved from learning analytics systems. For instance, the next instructor contacted low-performing students who did not submit an assignment on time or failed a quiz:

I would identify underperforming students who failed the quiz or did not submit the assignment on time, and probably contact those specific students, asking whether they understood the assignment and whether they have any unanswered questions. (I11, Female)

While the previous instructor mentioned approaching specific students who need extra assistance, the next instructor stated that data about students who struggle with the course assignments would lead her to approach the whole class to suggest them additional guidance:

I tried to keep track of students' performance through the Moodle learning analytics system. If I found out that several students failed the opening quiz, for example, I contacted the whole class, probably via a collective email, and suggested them some extra resources and assistance (I29, Female).

Not surprisingly, referring to their F2F teaching, instructors stated they would contact students in person*,* initiating *"*a one-on-one conversation with under-performing students" (I97, Female), while during ERT they stated they would contact students via online platforms, "preferably via synchronous technology like Zoom" (I40, Male).

Adjusting course requirements for future students - only ERT

The second type of data-driven decision that was repeatedly mentioned by the instructors was to adjust the course requirements to better suit remote teaching and learning. This theme was linked to the "course resources" dimension of educational data. The main sources from which the instructors collected data to support this decision were emails sent by students to the instructor and posts on the discussion forums. This decision was apparent only with reference to ERT; it was mentioned in 22% of the citations that referred to this mode.

While the previous theme referred to decisions to be taken in real-time, this theme refers to decisions taken in retrospect, which may help future students. For example, the next instructor revealed how students' emails led him to make changes in the course requirements for the next semester:

I will probably make some changes towards the next semester in the parts of the course that require modifications to better suit this new mode of learning online. This semester I received two or three emails from students who struggled to find partners to perform the group assignment with and also struggled to find time to meet online. These emails made me re-think about students' needs in the current period and I have made up my mind to make some changes to this assignment so that next semester students would be able to choose whether to conduct this assignment individually or in groups. (I99, Male)

Another instructor revealed how reading students' posts on the discussion forum made her realize the need to change the final project's requirements:

Since the transition to online, I try to follow up on students' correspondence on the discussion forum. Reading their posts made me realize what they are dealing with during this challenging time, and how can I assist them. Most of the correspondence was [sic] about the final project. Students complained that the project is too complicated and time-consuming. I decided to make several changes including linking the project to students' daily lives so that it would be easier for them to find a topic, and I also decided to clarify the requirements more, and reduce the number of pages and the number of references. (I28, Female)

One instructor claimed that the broader access to data while teaching online made him realize the need to adjust the course to the current educational needs of students:

I think that now we have more access to students' thoughts, feedback, actions […] During the online lecture I read some of the posts on the chat, so I have a clue about which parts of the lecture students have difficulties with. I believe this raises the level of curiosity and may lead to the will to make changes in the course requirements, assignments, and readings. (I39, Male)

Another participant explained how the transfer to ERT made instructors, who are usually "not enthusiastic about making changes in their courses," face the need to adjust their courses to the current era:

[...] there is an overall understanding that the transfer to online teaching requires some major changes, and suddenly instructors are more willing to consider taking the time to adjust their courses to this new digital environment […] In my case, I guess I plan to adjust some of the requirements to better suit students' needs, like reducing the number of quizzes or simplifying the final assignment. (I100, Male)

Promoting collaborations among students—mostly ERT

The third type of data-driven decision that was repeatedly mentioned by the instructors was designing course activities that promote collaboration among students. This theme was linked to the "collaborative learning" dimension of educational data. The main sources from which the instructors collected data were students' participation patterns and chat correspondence during the synchronous online lectures. This decision was apparent mostly with reference to the ERT mode; it was mentioned in 28% of the citations that referred to the ERT mode, and only in 9% of the citations that referred to the F2F teaching mode.

The respondents who referred to this decision with reference to the ERT mode explicitly mentioned two types of collaborative activities they have incorporated into their courses. The first collaborative activity was to offer students the opportunity to work in small groups on a joint learning outcome. One instructor revealed how she got the idea from reading students' correspondence in the public chat during the synchronous session:

I got this advice from a colleague of mine to start saving the chat correspondence from my online lectures. After the lecture, I started reading all the posts and the thing that most caught my eye was that students were eager to hear what their friends are thinking, feeling, doing [...] It made me think about how these students miss the direct connection with their peers, and I decided to allow them to work on the course assignments in small teams so they will have more opportunities to interact with each other. (I35, Female)

Another instructor also mentioned relying on students' chat correspondence to make decisions about promoting collaborative activities:

I watch how students behave during the online sessions. One thing I have noticed is that most of them ask questions on the chat during Zoom sessions. Students probably feel like they don't have enough support or connections with their classmates since there are no on-site classes. So, I started to put students into small groups, so they could benefit from direct interaction with their peers. I gave each small group a task, asked them to jointly think of a solution to a known problem, and then present their solution to the whole class. (I91, Male)

The second collaborative activity that the instructors promoted was to offer students the opportunity to provide each other with peer assessment. One instructor mentioned she decided to promote peer assessment activities as a response to students' low participation during synchronous sessions:

I have noticed that some of the students seemed completely disconnected during the online lecture, most of them did not look at the screen at all, did not participate in the discussions […] To increase student engagement, I decided to ask them to answer two short questions before each lecture. During the lecture, I devoted time to peer learning activities, where each pair of students exchanged their answers and evaluated their peer's work. The students loved this activity. (I1, Female)

Supporting students socially and emotionally—mostly ERT

The fourth type of data-driven decision that was repeatedly mentioned by the instructors was contacting students to offer them social and emotional support. This theme was linked to the "social and emotional support" dimension of educational data. The main sources from which the instructors collected data were students' emails, posts on discussion forums, and chat correspondence. This decision was apparent mostly with reference to the ERT mode; it was mentioned in 29% of the citations that referred to the ERT mode and in only 8% of the citations that referred to the F2F teaching mode.

While referring to the ERT mode, the instructors revealed their concerns that the physical distance between learners, and between them and the teaching staff, "decreases personal interactions with students" (I45, Male), and the "sense of belonging to a learning community" (I70, Male). Accordingly, an action that was repeatedly mentioned by the instructors was contacting individual students to personally provide them with the support they need. Below are two examples:

I still find the online situation awkward and isolating. I believe students feel the same way. During the semester I read a lot of posts and chat correspondence in which students expressed their lack of motivation, their anxieties, and concerns. I realized the need to provide them with extra support, and in most cases I reached out to those students personally, via a private email, suggesting to meet them virtually for an online office hour and tried my best to help them from my own experience. (I32, Female)

Many of my students have personal/financial/emotional problems. Some of them approached me through emails and some expressed their difficulties on the course's discussion forum. In both cases, I contacted those students personally to see if there is anything I can help them with. (I2, Male)

Other instructors mentioned contacting students with the purpose to refer them to professional counseling, such as “college-offered help from the advising center or the school social workers” (I73, Female), acknowledging that “many of them [the students] do need it” (I72, Male).

Two other instructors chose to contact the entire class to provide social and emotional support. The first instructor chose to contact students via a collective email:

I feel like there is not enough interaction between the students and between them and the teaching staff. This is why I make sure to contact my students with a weekly email in which I express interest in their well-being, update them on our progress, and of course invite them to offer ideas for improvement. (I68, Female)

The second instructor expressed his intention to contact all students and collect data about their mental health via surveys:

They [the students] cannot learn if they are not in good mental health [sic]. Maybe [I will] send all students a pre- and a mid-course survey to check […] what issues they would like to get help with. (I5, Male)

Several instructors linked their decisions to the unfamiliar and confusing situation that COVID-19 has brought along with it. Some referred to the pandemic openly:

A few students reached out about emotional issues, following the ongoing lockdowns due to the coronavirus pandemic. (I1, Female)

While others, such as Instructor 12, referred to the pandemic covertly:

In the online version of my course, I guess I make more efforts to understand […] how they [the students] are feeling in their new daily routine. We are all confused with this new reality we are forced to be in, and we all try to deal with this new situation. (I12, Female)

To sum up, the four themes that emerged from our data are summarized in Table 2.

Table 2

The Four Themes for the Types of Data-driven Decisions, in F2F and ERT

	Data-driven decisions	**Explanation**	**Teaching mode**	**Instructional dimension**	**Data source**
1	Providing real-time educational assistance	Contacting students in real-time to suggest educational guidance	F2F + ERT	Course resources	Participation patterns, grades
2	Adjusting course requirements for future students	Adjusting the requirements of the course in retrospect, to better suit the ERT mode	Only ERT	Course resources	Emails, posts on discussion forums
3	Promoting collaborations	Designing course activities that promote collaboration among students	Mostly ERT	Collaborative learning	Participation patterns, chat correspondence
4	Supporting students socially and emotionally	Contacting students to suggest social and emotional support	Mostly ERT	Social and emotional support	Emails, posts, chat correspondence

Discussion

This study was carried out during the first year of the COVID-19 pandemic outbreak when ERT was the dominant form of instruction on campuses around the globe. As our qualitative findings suggest, in F2F teaching the instructors focused mainly on decisions that relate to academic aspects, such as providing students with real-time educational guidance. Conversely, in ERT, the instructors described a wider range of data sources and a wider range of data-driven decisions, from academic-related issues (such as adjusting the course requirements) to socio-emotional-related issues (such as promoting collaborations among students).

This may be attributed to the notion that online environments provide access to a wide range of data about learners from various sources (Cerro Martínez et al., 2020; Shibani et al., 2020; Tsai et al., 2019), and that analyzing such data can support and guide instructors' decision-making (Archer & Barnes, 2017; Gašević et al., 2016; Gutiérrez et al., 2020). Hence, the access to varied educational data while teaching online might have encouraged our participants to make data-driven decisions. These results are consistent with a recent study that surveyed higher education instructors regarding their interest in learners' data and willingness to make decisions. The authors have concluded that instructors showed more interest in learners' data and an overall willingness to make decisions while teaching online, compared with F2F teaching (Usher et al., 2021b).

The analysis has raised four themes for the types of data-driven decisions the instructors have made in their courses. In F2F teaching, the instructors mostly contacted students in real-time to offer them educational guidance and assistance with the course content and assignments. In ERT, the instructors mostly adjusted the course requirements to better suit remote teaching and learning, promoted collaborations among students, and offered them social and emotional support.

The great emphasis placed on nonacademic issues (such as social and emotional aspects of learning) in times of emergency has been reflected in four recently published articles. The first two articles highlight the students' perspectives. Barrot and colleagues (2021) indicated that the most urgent challenges students encountered during the pandemic were related to their mental health; they experienced anxiety not only from the threats of COVID-19 itself, but also from social and physical restrictions, unfamiliarity with new learning platforms, and concerns about financial resources. Ezra and colleagues (2021) reported a lack of a sense of community or connectedness and social difficulties among higher education students during ERT. The last two articles highlight the instructors' perspective. Walsh and colleagues (2021) reported that faculty members found themselves making deeper, and more personal connections with their students during the ERT, helping them with mental, social, and health issues. Lastly, a quantitative study indicated that during ERT instructors showed a willingness to make decisions mostly based on data about learners' needs for social and emotional support (Usher et al., 2021b).

This inclination to make data-driven decisions regarding nonacademic issues (such as social and emotional aspects of learning) during ERT can be linked to the challenges online learners are facing, especially in times of emergency, where extreme measures, such as quarantine or lockdown, are taken (Ezra et al., 2021). These unique circumstances could aggravate the already known challenges experienced during online learning, such as a lack of support and a sense of loneliness (Kumar & Johnson, 2019; Usher et al., 2021a). Hence, the instructors in this study may have been concerned about their online students' struggles at such times, which made them pay more attention to socio-emotional issues and make data-driven decisions that relate to these matters.

This study's findings may suggest that there is an opportunity for educational decision-makers to implement a data-driven instructional initiative. For such an initiative to be successful, the educational data should be made accessible to instructors in a way that would make it easy for them to understand the data and make informed decisions (Michaeli et al., 2020; Ndukwe & Daniel, 2020).

Instructors should be encouraged to continue using different types of educational data from different sources for educational decision-making, even with the gradual return to campus and the transition back from ERT to hybrid or F2F teaching. This is especially true for educational data based on students' social, mental, and emotional well-being, which seem to be of special interest to instructors teaching remotely. Moreover, we believe that there is a need for collaborative workshops for instructors aimed at improving their data literacy, further familiarizing them with usage patterns and with different ways to act upon data. This way, the instructors would understand the information that is accessible to them, use data in a broad and efficient context, and connect it to actions that are aimed to improve their courses, both in emergencies and in routine.

Limitations and Further Research

This study has several limitations, which might be seen as a potential for future research. The first limitation of this study derives from its research tool (i.e., an online questionnaire), in which respondents were asked to self-report their perceptions in the context of a single course and regarding its two modes of teaching. Self-reporting tools might suffer from recall bias, social desirability bias, and errors in self-observation. The second limitation relates to the research population. Our qualitative findings were obtained from the perspective of 109 higher education instructors. Thus, we suggest future work on instructors' data-driven decision-making to expand the research settings to a broader, more representative research sample of the population and to examine more clearly defined populations. This is not only to evaluate the extension of the findings of this study, but also to explore further themes related to higher education instructors' data-driven decision-making.

Declarations

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