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Interaction types in distance learning

Experiences and perspectives of Austrian EFL student teachers

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The present paper examined how 107 Austrian EFL student teachers experienced online interaction types in distance learning during the COVID-19 university lockdown in March 2020. Four different online interaction types (learner-self, learner-interface, learner-content, and learner-support) were derived from the pertinent literature and converted into both open and closed online questionnaire items (Ally, 2011; Boling, Hough, Krinsky, Saleem, & Stevens, 2012; Zheng, Lin, & Kwon, 2020). Using a mixed-methods convergent parallel research design, closed items were examined quantitatively, with a focus on response distributions and the homogeneity of the scales representing the four types; a qualitative analysis of the open items complemented the quantitative results and explored response patterns and response categories in more detail. Thus, the interpretations are based on a parallelly converging evaluation of both data types. Triangulation of the results suggests that student teachers regard regular guidance by instructors and a shift from teaching to learning materials including cognitively demanding tasks as crucial for their learning process. Whereas student teachers reported positive experiences with regard to learner-support interaction, peer interaction was reported as deficient. The paper concludes with a discussion of implications for online course development and delivery as well as avenues for future research.

KEYWORDS: online interaction, EFL teacher training, distance teaching, mixed-methods convergent parallel design

1. Introduction

The COVID-19 pandemic has given new momentum to the debate around the potential of distance learning as a primary means of course delivery (Dhawan, 2020; Youngjoo & Jang, 2020). Such a shift from face-to-face to online teaching and learning, however, is much disputed. And although distance learning could be regarded as a mere subset of general learning (Anderson, 2011), it is particularly challenging to study programmes for which social interaction is indispensable, like in EFL teacher education (Garrison, Anderson, & Archer, 2000; Hampel & Stickler, 2012; Pu, 2020; Zheng, Lin, & Kwon, 2020). This raises the question of how social interaction can be implemented in online course delivery as part of a distance learning scenario. Following Boling, Hough, Krinsky, Saleem, and Stevens (2012), who claimed already ten years ago that the effectiveness of online interaction was largely unexplored, this paper examines how Austrian EFL student teachers experienced online interaction in distance learning, focusing on the following four interaction types (1).

(1) (a) learner-self interaction
    (b) learner-interface interaction
    (c) learner-content interaction
    (d) learner-support interaction

The four types synthesize various approaches to online learning and can be regarded as suitable for pure language classes and content-based courses, which both play an important role in the curricula for Austrian EFL student teachers. Type (a) draws on Zheng et al.'s (2020) as well as Jaggars and Xu`s (2016) higher education studies on student-level, instructor-level, and course-level interaction. Their data suggest that learner-self interaction in particular impacts on student performance. Types (b) to (d) mirror both Ally's (2011) tiered model of interaction in online learning and Boling et al.'s (2012) approach to online learning experiences. Based on behaviourist, cognitivist, constructivist, and connectivist schools of learning, Ally proposed a distinction into lower-level and higher-level interaction, with learner-interface interaction at the lowest level, followed by learner-content and learner-support interaction. The different levels are characterized by the extent to which learners process the information provided in order to facilitate long-term retention. Boling et al. (2012), in a similar vein, suggested that online learning experiences are influenced substantially by the involvement of higher order cognitive skills.

In sum, the study aims to describe ways in which the quality of further online elements of EFL teacher education programmes can be enhanced by providing an evaluation beyond the individual course level and therefore supports educators in conveying strategically chosen content through effective pedagogies (Darling-Hammond & Hammerness, 2007).

2. Theoretical background

It is a classic formula in EFL didactics that learning processes unfold through learners encountering input, interacting among themselves, with materials, or an instructor, in order to finally produce output (Gass & Mackey, 2015). Interaction, therefore, has had its central place in EFL learning for almost 40 years (Long, 1983), and it has been proven to be instrumental in making input comprehensible (Mackey, 1999), to balance accuracy and fluency, foster willingness to communicate, inhibit anxiety, and facilitate communicative learning (Ellis & Shintani, 2014). Some researchers even claim interaction would also be key to the acquisition of lexicogrammar (Larsen-Freeman, 2015). The power of interaction in EFL didactics is not limited to its cognitive facilitation, though; it also reflects the pivotal role of participation in any language learning according to sociocultural theory (Lantolf, 2000; Vygotsky, 1987). This means that language learning emerges in rather than as a result of participatory learning. In short, interaction is an inherent and mediating part of language acquisition but also provides cognitively facilitating conditions for it.

Interaction in the interactional or sociocultural paradigm

Within the interactional or sociocultural paradigm, EFL didactics have long explored central aspects such as input modification, collaboration, negotiation for meaning, corrective feedback, scaffolding, or translanguaging. And it is widely agreed that such aspects are indispensable for successful EFL teaching and learning (Hall, 2010); this is probably true for EFL online course delivery, too, as one of the potential benefits that might be derived from working in an online setting is the use of multiple modalities (Ciekanski & Chanier, 2008). Being able to explore complex issues using text, audio, and video can support the learners in gaining fuller understanding of the subject matter. In addition, applications which allow for both audio and text chat to negotiate meaning and communicate with peers support the instructor in stimulating activities which are more process-oriented and collaborative in nature (Blake, 2005).

Student-level, instructor-level, and course-level factors

As already stated above, there are various approaches which need to be taken into account when examining interaction in online settings. One distinction separates student-level, instructor-level, or course-level factors (Zheng et al., 2020). As the effects of teacher characteristics on student learning outcomes have not yet been explored systematically (Zhang & Lin, 2019), only student-level and course-level variables were selected for further investigation in this study. One student-related aspect conducive to online learning processes is the number and duration of log-ins. However, results are mixed (Zheng et al., 2020) and only partly include other factors which are likely to co-determine the learning outcome. Moreover, at the other end of the scale, distraction and lack of self-discipline have been described as hindering the learning process (Zheng et al., 2020). With regard to course-level factors, course organization and presentation, learning objectives and assessments, interpersonal interaction, and technology have been identified as those that impact student performance (Jaggars & Xu, 2016), with interpersonal interaction exerting a significant positive effect on students' final grades. In addition, factors such as a shift from a teaching to a learning paradigm and involvement of tasks requiring higher order cognitive skills have proved to constitute effective online learning experiences (Boling et al., 2012).

Levels of interaction in online learning

Another distinction which was used to establish the categories for this study was derived from Anderson's (Anderson, 2011) and Ally's (Ally, 2011) works on interaction in online learning. Anderson's model explores the relationship between the human actors, learners as well as teachers, and their interactions with the content and highlights the importance of personal relationships and regular sessions. Moreover, with reference to Prensky (2001), he provides an extensive list of particular learning activities which he considers to be suitable to practise a particular skill, thereby suggesting ways in which learners can be supported in their learning process. Ally (2011), in a similar vein, argues that the design of learning materials in an online setting should be guided by specific components of learning theories which target either the what, the how, or the why. Among those components are the clear definition of learning outcomes, the inclusion of both formative and summative assessment, the sequencing of learning materials, the teaching of online learning strategies, the use of differentiated learning materials, and the design of meaningful activities which promote high-level processing. He also stresses the importance of collaborative, cooperative and autonomous learning. In his tiered model of interaction in online learning, Ally extends Hirumi's (2002) three-layered framework by adding levels of complexity of interactions, three of which were modelled in the present study. First, there is learner-interface interaction, located between the learner and the device used to access content and interact at the lowest level. This is followed by learner-content interaction, in which information is processed and knowledge acquired, and learner-support interaction, which can take the forms of learner-learner and learner-instructor interaction. On the highest level of complexity, real-life-transfer of learning is supposed to take place. This type is labelled as learner-context interaction and refers to opportunities which should be provided for learners to apply their knowledge in real-life situations.

In the research question guiding our empirical study we thus ask how Austrian EFL student teachers experienced the above mentioned four types of online interaction in distance learning. Our data are supposed to provide insight into aspects as well as patterns supporting and hindering online learning processes, so that empirically founded and theoretically informed choices with regard to future online teaching and learning can be made. Moreover, we were aiming to find out if the items used in the survey reflected the constructs learner-content and learner-support interaction appropriately.

3. Method

Sample

107 student teachers of English were convenience-sampled from the two University Colleges as well as the University involved in the secondary study programme in Linz, Upper Austria. Since the programme is delivered as a joint-honours-degree, participants were fully enrolled in all three institutions. All participants could be considered to be Central European (CE), and there were no ethnicity issues interfering with data collection and analysis. Of these 107 students, 85 identified as cisgender women, 22 as cisgender men, and none as non-binary or diverse. All participants filled out both the quantitative and the qualitative part of the online survey anonymously, voluntarily and with explicit consent, but without any financial renumeration. Data collection and analysis procedures were approved and funded by both University Colleges involved. Their ethical and institutional guidelines regarding the rights of research participants, in keeping with the APA Ethics Code Standard (American Psychological Association, 2017), were adhered to.
At the time of the survey, all participants were studying EFL as part of their four-year Bachelor teacher education study programme in one of the five Austrian university clusters. Students were in the 2nd, 4th, 6th, and 8th semester of their studies and had all gone through six weeks of distance teaching and learning.

Instrument

The quantitative part of the online survey consisted of 13 five-point Likert items. They are summarised in Table 1, together with the types of interaction they operationalised. The items were derived from Boling et al., 2012; Hirumi, 2002; Zheng et al., 2020 but had not been piloted with regard to the different types of online interaction. The results section will present item analyses and exploratory factor analyses for learner-content-interaction and learner-support-interaction. We do not assume, though, any particular latent construct underlying all 13 items but will exploratorily analyse them for consistency.

TAB. 1. *Types of Interaction and their Operationalisation in Quantitative Likert Items*

	Type of Interaction and Source	Survey Likert Items
(a)	Learner-self Interaction Zheng et al. (2020)	Please tick which of the following positive / negative experiences with distance learning in English applied to you. *1. Regular log-ins (e.g., time spent logged into Moodle working individually on tasks) for longer periods of time (appr. 2 hours a week).* *2. Significant amount of time off-task due to a range of distractions, lack of self-discipline.*

	Type of Interaction and Source	Survey Likert Items
(b)	Learner-interface Interaction Ally (2011) Hirumi (2002)	Which of the following tools, apps, and platforms have worked well? 3. *Moodle, Zoom, BigBlueButton, Google, Teams, WebX, Skype, Dropbox*
(c)	Learner-content Interaction Ally (2011) Boling et al. (2012) Zheng et al. (2020)	Please tick which of the following positive / negative experiences with distance learning in English applied to you. *4. Clarity regarding learning objectives and assessments.* *5. Good course organization and presentation.* *6. Variety of tasks on different levels of complexity.* *7. Activities which encourage students' engagement and in-depth thinking.* *8. Teacher's lack of experience in using online tools.* *9. No clear distinction between learning materials with a focus on the course objectives and additional resources.*
(d)	Learner-support Interaction Ally (2011) Boling et al. (2012) Zheng et al. (2020)	Please tick which of the following positive / negative experiences with distance learning in English applied to you. *10. Interpersonal interaction: collaboration, feedback.* *11. Responding to others' work in online discussions.* *12. Limited amount of peer interactions.* *13. Inefficient student-teacher communication.*

As we can see, learner-self interaction was represented by only two items, based on aspects which had proved to play a decisive role in learning processes in recent studies (Zheng et al., 2020). Learner-interface interaction focused on the eight tools which were made available for the participants in the study by the institutions involved. These items reflect the actual range of technical support provided at the three institutions in question and thus was a pragmatic rather than research-based selection; it was hoped that more detailed information covering various aspects of this type of interaction could be obtained by means of the qualitative part of the study. Learner-content interaction was represented by items investigating the materials provided and the quality of their use in the online setting (Ally, 2011; Boling, 2012; Zheng, 2020). Learner-support interaction included four items that reflected collaborative learning processes (Ally, 2011; Boling, 2012; Zheng, 2020). The choice of items for each type for interaction was discussed in the team of researchers after conducting the literature review. Negatively valenced items were re-scaled prior to statistical analyses.

As the items had not been validated in a pilot study, qualitative data were elicited through two open items in the online questionnaire. It was assumed that the results could be used to further develop the scales if required. The statements are given in (2).

(2) (a) Describe positive experiences with distance learning in English you've had.
(b) Describe negative experiences with distance learning in English you've had.

4. Design

The study employed a mixed-methods convergent parallel design (Creswell & Plano, 2006; Creswell, Plano Clark, Gutmann, & Hanson, 2002; Riazi & Candlin, 2014). The rationale behind this choice was the assumption that parallelly triangulating quantitative and qualitative data would produce insights not gleaned from one of these fields alone. The goal of the quantitative part was to summarise response patterns and distributions in the data. The goal of the qualitative part was to shed light on these patterns by using deductive categories in order to create inductive response categories. The proactive triangulation of both types of data was supposed to inform the derivation of didactic implications and the discussion of avenues for future research in the final sections of this paper. Both quantitative and qualitative data were obtained from an online survey simultaneously (Leiner, 2019) during the lock-down phase of the summer semester 2020. After inspection of the data set, incomplete and suspicious cases were eliminated, leaving107 cases to further analysis.

Coding and Quantitative Data Analysis

Quantitative data were analysed using the software R, a language and environment for statistical computing and graphics, version 4.0.3 (R Core Team, 2020), in particular the packages *HH*, version 3.1-35 (Heiberger, 2020), *likert*, version 1.3.5 (Bryer & Speerschneider, 2016), and psych, version 2.0.12 (Revelle, 2020). Following Rädiker and Kuckartz (2019) as well as Nassaji (2020), qualitative data were analysed using the software MAXQDA (20.0.8, VERBI Software, 2018); this was supposed to secure data validity, credibility, and academic rigor.

Likert responses were first coded numerically, ranging from *totally agree* (1) to *totally disagree* (5); For the items examining learner-interface interaction, these five categories were complemented by the sixth category *did not use* (-1). Numerical Likert responses were treated as interval scaled. Some items were valanced positive, some negative. For statistical analyses, negative items were re-scaled, then all variables were standardised (*z*-scored) to unit variance. In a first step of the data analysis, the distribution of the responses was examined and visualised. In addition to that, learner-content interaction and learner-support interaction were treated as a scale and analysed for their internal consistency and unidimensionality. Internal consistency was assessed through Cronbach's α (Kline, 1999), while unidimensionality and potential latent factors were examined using Exploratory Factor Analysis (EFA; Watkins, 2020). In order to assess the scales' suitability for such unsupervised clustering techniques, correlation matrices, Bartlett's test of sphericity (Bartlett, 1950) as well as the Kaiser-Meyer-Olkin-index of sampling adequacy (Czerny & Kaiser, 1977) were inspected. The number of factors was determined using both Parallel Analysis (Horn, 1965) and Velicer's Minimum Average Partial Test (MAP; Velicer, 1976). Factors were extracted using minimum residuals, producing solutions very similar to maximum likelihood estimation, even for small sample sizes and badly behaved correlation matrices (Gonulal & Loewen, 2015). Factor loadings > 0.4 were considered substantial but retained only if more than one variable loaded onto them (Costello & Osborne, 2005; Fabrigar et al., 1999).

Coding and Qualitative Data Analysis

The qualitative data were submitted to a content analysis, with deductive category application and inductive category development (see Appendix A; Mayring, 2014). The analysis followed a cyclical procedure of developing categories, coding, discussing, and recoding the data. First, the theoretically motivated initial five types of online interaction served as deductive categories (Ally, 2011; Anderson, 2011). Based on these deductive categories, a selection of student responses was trial-coded by two coders. Then, personal interpretations of category definitions were discussed, and codes were revised. Following this trial coding, each of the coders coded the entire material separately. Following an intercoder agreement data analysis, which yielded rather low Kappa values (Brennan & Prediger, 1981) at high percentage segment levels (Table 2), code assignments that did not match were discussed and deleted until full agreement was reached (O'Connor & Joffe, 2020).

TAB. 2. *Intercoder Agreement Data Analysis for Deductive Categories and Number of Codes per Coder*

	Deductive Categories	Coder 1	Coder 2	Σ	Kappa (κ)
(a)	Learner-self Interaction	73	72	145	0.15 / 0.21
(b)	Learner-interface Interaction	81	64	145	Min. code overlapping rate of 90% at segment level.
(c)	Learner-content Interaction	179	138	317	0.50 / 0.54
(d)	Learner-support Interaction	108	116	224	Min. code overlapping rate of 10% at segment level.
(e)	Learner-context Interaction	5	3	8	
	Σ	446	393	839	

Note. For details on Kappa see Appendix B

After deletion of the code assignments that did not match, 252 codes remained, and the coders inductively developed 12 final subcategories for four types of online interaction (see Table 3 and Appendix A).

TAB. 3. *Deductive and Inductive Coding Categories*

	Deductive Categories	Inductive Categories
(a)	Learner-self Interaction	• Freedom & independence • Time efficiency • Personal well-being
(b)	Learner-interface Interaction	• Tools • Infrastructure
(c)	Learner-content Interaction	• Task quality • Task quantity & workload • Objectives & assessment • Class organization • Methods
(d)	Learner-support Interaction	• Instructor-interaction • Peer-interaction
(e)	Learner-context Interaction	

Since the number of code assignments in the learner-context interaction category was rather limited, no subcategories were created for this form of interaction and it was not included in the triangulation of the results.

5. Results

We first assessed the internal consistency of the eleven items representing learner-self interaction, learner-content interaction as well as learner-support interaction. Their standardised Cronbach's α amounts to 0.86, 95% CI [0.81, 0.89], indicating a good consistency. From the eleven items, the two items reflecting learner-self-interaction and the item *peer interaction* show a rather skewed distribution, a moderate corrected item-total correlation only ($r_\tau < .40$) and a tendency to increase standardised α slightly when dropped; in other words, they do not seem to fit the scale as well as the other items. For each of the subsections we obtained the following results.

Learner-Self Interaction

Recall that learner-self interaction was quantitatively assessed through students' regular log-ins as well as their lack of self-discipline. Qualitatively, it was assessed through the open questions about positive and negative experiences (2). It turns out that most students rated log-ins as being a positive experience, while for a substantial number of students a perceived lack of self-discipline constituted a negative experience in learner-self interaction. From the open questions, three inductive subcategories could be created for learner-self interaction, namely *freedom and independence, time efficiency*, and *personal well-being*. These categories partly confirm the trend from the quantitative analysis. First, as part of the freedom and independence as well as time efficiency category, we could find positive reports about regular attendance, daily routines, commuting, as well as flexibility in time management and learning progression. This mirrors the appreciation of regular log-ins in the quantitative data. Second, the qualitative data suggested that self-discipline and distraction was perceived as a challenge by many, also reflecting the trend from the quantitative analysis. This is illustrated by the examples of student statements given in (3).

(3) (a) "My negative experiences mostly have to do with myself, as I sometimes struggle with self-discipline at home."
(b) "I noticed how essential regular attendance is for me, without pre-fixed classes I often fail to structure my workload."
(c) "I do not perceive my bedroom as a working room; therefore, I get distracted easily. University offers a much better working environment".

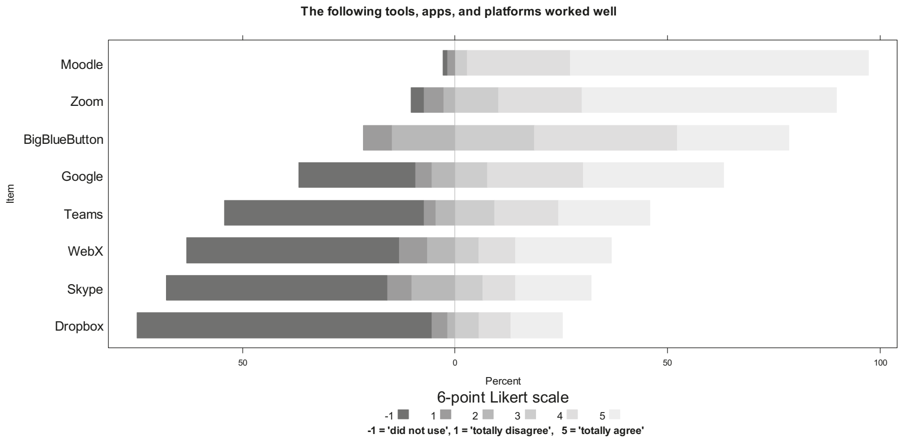
In addition to that, the qualitative data suggest a rather negative evaluation of the students' personal well-being during the distance teaching period, including statements about their emotional state and increasing levels of frustration due to too much workload. In sum, learner-self interaction seems to benefit from regular log-ins and was perceived positively in terms of freedom, independence, and time efficiency. At the same time, though, learner-self interaction suffered from emotional strains and work-related stress.

Learner-Interface Interaction

Learner-interface interaction was quantitatively measured through eight closed Likert items, including (-1) for *did not use*. Qualitatively, this interaction was reflected again in the two open items in (2). The quantitative replies show substantial variability in the students' use and appreciation of the eight tools in question (Figure 1).

At the top of Figure 1 we can see that almost all the students used and liked Moodle. The bottom four tools, in contrast, were not used by about 50% of the students, but around half of those who used them rated them positively. When disentangling frequency of usage and appreciation, it turns out that Moodle, Zoom, Google, and Teams were rated positively overall, with an overwhelming majority stating that these tools worked well (*totally agree*, *agree*), while Skype, BigBlueButton, WebX as well as Dropbox received rather mixed ratings.

FIG. 1. *Divergent Stacked Barplot for the Distribution of the Six-Point Likert Responses to the 8 Items Representing Learner-Interface Interaction*



For learner-interface interaction, qualitative content analyses produced the two inductive categories *tools* and *infrastructure*. Tools-related responses include appreciative statements of the tools used in terms of communicative and technical functionality, but also critical evaluations of internet access and technical devices needed for distance learning during lockdown. This is illustrated in (4).

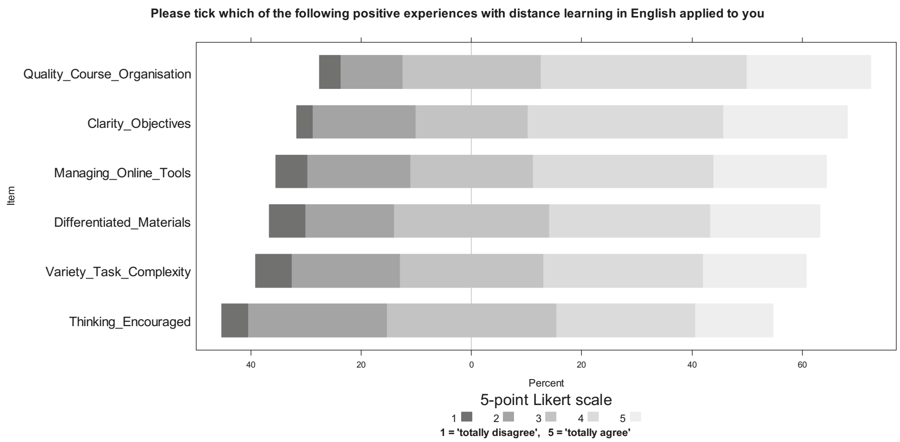
(4) (a) "I think it is surprising how well the presentations and classes work on google meets etc.."
(b) "Interruptions and technical problems with BBB."
(c) "I consider bad internet connection, insufficient microphones, malfunctioning cameras etc. as technological barriers."

In sum, it appears as though learner-interface interaction was positively influenced by those tools that were frequently and successfully used, while students felt impaired at the same time by general technical issues.

Learner-Content Interaction

Learner-content interaction was quantitatively measured through six survey items. Figure 2 illustrates the distribution of the five-point Likert responses to these items.

FIG. 2. *Divergent Stacked Barplot for the Distribution of the Five-Point Likert Responses to the 6 Items representing Learner-Content Interaction*



As we can see, the experience with these six aspects of learner-content interaction were very comparable and predominantly positive (right-hand-side of the graph), with overall course quality being rated best (top bar) and task complexity and encouragement to think rated worst (bottom bars). This homogeneity in the responses is reflected in the scale's good internal consistency, with standardised Cronbach's $\alpha = 0.84$, 95% CI [0.77, 0.88]. Managing online tools, though, does not correlate as well with the scale as the other five variables do (item-total correlation $r_\tau = .46$ and increased α when dropped). An EFA on the correlation matrix (Bartlett χ^2 (15) = 220.83, $p < .001$, determinant > 0.0001, $KMO = 0.85$) of all six items from this subscale (cf. Table 1) suggests that there was no underlying latent structure behind learner-content interaction. The most appropriate solution was monofactorial in both a parallel analysis (Horn, 1965) and Velicer's minimum average partial test (MAP, $RMSEA < .05$, $TLI > .90$). The variable *managing online tools*, however, displays the weakest loading on such a monofactorial solution ($\lambda = .50$). The trend visible in Figure 1 is partly mirrored in the qualitative data. Among the four qualitative inductive categories, we can find, for instance, *task quality* and *task quantity*. Within these two categories, we received rather critical responses about reduced quality in terms of complexity as well as overwhelming workload (5).

(5) (a) "Most tasks include reading and answering a set of questions. Not exactly a negative thing, but I think the actual courses at university would have included more complex tasks."
(b) "Hard to get specific information and clarity."
(c) "I feel like I'm snowed under with work."
(d) "Work has to be done almost exclusively by students, only ppt file with no further explanation, only statements like "please research xy" or "look at xy"."

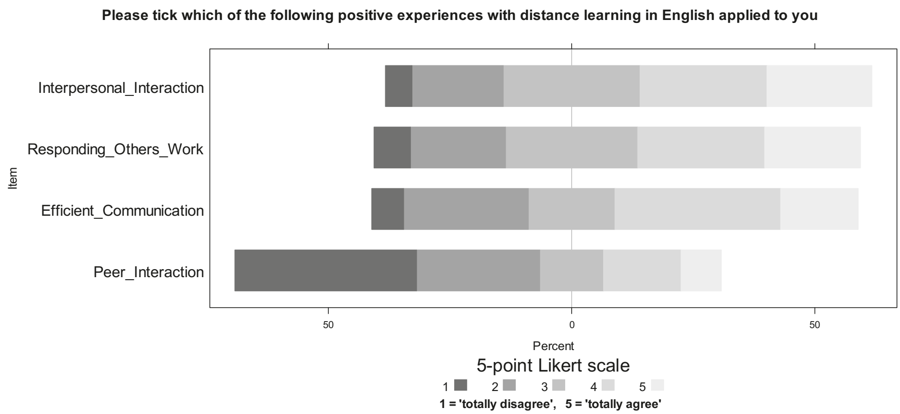
Another set of replies was inductively coded *objectives*, and some students reported that there were too many assignments and a lack of clarity and information in terms of objectives, exam content and procedure. This somehow contradicts the rather positive quantitative rating of the clarity of course objectives in Figure 2. Yet another inductive category was *class organisation*, and while some students seem to appreciate this aspect, others complained about it.

Finally, learner-content interaction categories also included responses about methods and tools, and these, too, were mixed. One the one hand, some students appreciated content, such as pre-recorded video tutorials and lively forum discussions, while others complained that interactive discussions hardly ever happened due to the lecturer's time management problems. When looking at both qualitative and quantitative data, learner content interaction appears to be ambiguous. In almost all the categories we find both positive and negative evaluations, and it seems as though no clear trend can be derived from our data.

Learner-Support Interaction

The last type of online interaction we looked at more closely was learner-support interaction. Figure 3 illustrates the distribution of the five-point Likert responses to this scale.

FIG. 3. *Divergent Stacked Barplot for the Distribution of the Five-Point Likert Responses to the 4 Items representing Learner-Support Interaction*



As we can see, interpersonal interaction, responding to others' work, and efficient communication were rated similarly. Peer interaction, in contrast, was rated much more negatively; almost 40% indicated that they totally disagreed with this being a positive experience. The qualitative content analysis suggests two kinds of learner-support interactions, namely *peer interaction* and *instructor interaction*, with both positive and negative statements about either category. Instructors would, for instance, be open to suggestions, keep communication going, and provide information when necessary. In contrast, also a lack of communication and availability was reported repeatedly and described as stressful and frustrating (6).

(6) (a) "Communication is frequent and clear."
(b) "Professors ask us for ideas and improvements."
(c) "Were always ready to answer questions."
(d) "Asking something after the lesson felt like bothering the teacher."
(e) "I seriously struggle with one course because the professor completely leaves us alone".
(f) "The professors' commitment and efforts to support us the best way possible".

Under *peer interaction*, we subsumed statements about the importance of exchanging ideas among fellow students and the importance of a learning community for support. On the one hand, such a community was reported to be difficult to activate and build, due to a lack of interaction, on the other hand, some students saw improvement in the course of the distance teaching phase. Overall, both quantitative and qualitative data suggest that both lecturer and peer interaction are important for learner-support interaction, and that students sometimes missed this dimension during online class delivery. Internal consistency analyses confirm the special status of the item peer interaction in the quantitative data, it being slightly off the scale (Cronbach's $\alpha = 0.75$, 95% CI [0.68,0.82]), with item-total correlation dropping to $r = .42$ when excluded. An EFA on the correlation matrix (Bartlett χ^2 (6) = 111.02, $p < .001$, determinant > 0.0001, $KMO = 0.72$) of all four items from this subscale (cf. Table 1) suggests that there was no underlying latent structure behind learner-support interaction. The most appropriate solution was monofactorial in both a parallel analysis (Horn, 1965) and Velicer's minimum average partial test (MAP, $RMSEA < .05$, $TLI > .90$). In this solution, the item peer interaction loads lowest on the one factor ($\lambda = .48$).

6. Discussion

Recall that the research question guiding this empirical study revolved around how Austrian EFL student teachers experienced four specific online interaction types during distance learning in the summer semester 2020. We were hoping to gain detailed insight as to how the different types of interaction were perceived, how well they represented one specific type, and what aspects of the four types of online interaction were covered in the students' responses.

Learner-self interaction emerged mainly from Zheng et al. (2020), who focusses on the importance of regularity with regard to guided learning periods and self-discipline as a decisive factor in the online learning process. Our data suggest that students perceived freedom, independence, and time efficiency in general and regular log-ins for longer periods of time, in particular, as beneficial for this type of interaction. In contrast, self-discipline was lacking. Student teachers seemed to benefit from the fact that they were provided with a clear time structure, could adopt their preferred learning style and spend time primarily on the tasks set, but it seems to be a very thin line between thoroughly enjoying this freedom and failing to make good use of it and consequently feeling left alone with all the work. It could, therefore, be rewarding to explore this aspect further by using instruments such as the Online Self-regulated Learning Questionnaire (Barnard et al., 2008), which aims at measuring students' ability to self-regulate their learning in blended or wholly web-based settings.

When taking a closer look at learner-interface interaction it is striking that, most likely due to a novelty effect, the main focus in the qualitative data is on the video-conferencing tools used. While the quantitative data suggest that this type of interaction was positively influenced by those tools that were frequently and successfully used, general technical issues seem to have hampered learner-interface interaction. Moodle scored top ratings in the closed items but did not seem to be worth mentioning explicitly in the open questions.

The quantitative analysis of the data on learner-content interaction indicated that the instructor's ability to deal with online tools might be regarded as a factor that differs in some way from the other aspects included in the scale. The inductive categories which could be established might provide a reason why, since it could be clearly seen that students focus on tasks, or, more precisely, on task quality and quantity, rather than the tools used to make them available in their answers. When triangulating qualitative and quantitative data, however, learner-content interaction remains ambiguous.

Finally, the closed items for learner-support interaction received rather positive ratings except for peer interaction, which does not correlate well with this scale. Moreover, peer interaction in the qualitative data was repeatedly reported as deficient. Both quantitative and qualitative data, though, indicate that *instructor support* as well as *peer support* display a distinct quality of learner-support interaction in distance learning. Referring to the concept of the professional learning community (Stoll, Bolam, McMahon, Wallace, & Thomas, 2006) in which members work "in an ongoing, reflective, collaborative, inclusive, learning-oriented, growth-promoting way" (p. 223) might help to explain why. Whereas instructors at least partly seemed to have found ways to make the learning process positive for the student teachers, distance learning was lacking social forms of interaction and solid exchange between the learners (Garrison et al., 2020). Overall, online or distance class delivery, apparently a fast-selling panacea of our times, is somewhat demystified in our data, when students report that in their experiences it was task quality rather than the tools used that made their day. In other words, technology does not make EFL didactics; it provides a delivery dimension, and it is perceived as such by learners. Based on the abundance of critical responses in both our qualitative and quantitative data, three implications for online course development and delivery will be discussed.

Firstly, our study suggests that distance learning course delivery might benefit from the provision of cyclical and synchronous online meetings rather than from asynchronous course designs where the students are expected to work on pre-set tasks without instructor support for a longer period of time. Regular meetings at shorter (e.g. weekly) intervals appear to be particularly important, not least because they can provide opportunities to clarify or update information about course objectives and exam requirements. Secondly, in EFL distance learning contexts there seems to be a need for a shift from task quantity to task quality. Instead of too many written tasks, often based on repetitive question-answer patterns, fewer assignments including more complex and thus cognitively more challenging tasks might be an option. Not only have tasks which require higher order cognitive skills proved effective in online learning experiences (Boling et al., 2012), such tasks may in fact be considered as vital components for professional learning. Thirdly, since the data indicate that the student teachers experienced peer interaction as deficient, it appears that any distance learning course design needs to address this issue. One way to compensate for this deficiency might be the provision of a course-specific online peer interaction space, where, in pre-scheduled timeslots, the students can share their online experiences with each other.

7. Conclusion

This study aimed to investigate how Austrian student teachers of English experienced online interaction types in distance learning during the summer term lockdown in 2020. It focusses on the experiences of a specific group of EFL learners rather than EFL teachers, and therefore provided insight into a field which, according to recent studies (ECML, 2021), should still be investigated further. While it showed how the students experienced the four different interaction types, highlighting a pivotal role of regular guidance by instructors and a deficit of peer interaction, there are also a number of limitations: First, our convenience sample was neither geographically nor demographically representative, as participants from only one institution in Austria were taking part. Second, as the scales used were specifically designed for our study, we can merely report the results of a piloting phase which has to be regarded as the starting point for further studies. Third, learner-context interaction, i.e., the category which describes when learners are allowed to apply what they learn in real life so that they can contextualize the information, was not given the attention it probably requires in teacher education due to the fact that items could not be derived from the literature used.

Given the current developments in both secondary and tertiary EFL online class delivery, the following avenues for future research can be outlined. First, peer interaction as one element of learner-support interaction should be examined in more detail. It would be interesting to explore EFL student teachers' perceptions of this type of interaction systematically, for example by disentangling whether they perceive a lack of opportunities or simply do not use such opportunities. Moreover, it could be examined how the perception of peer interaction is affected by delivery mode (face-to-face versus online delivery, Hampel & Stickler, 2012). Second, the correlation between a perceived quality of peer interaction in online teaching and the learners' development of language skills, especially speaking skills, could be empirically examined. This would involve testing in how far learner-interface tools are in fact conducive to language learning processes. Finally, the concept of learner-context interaction seems to require further investigation, which could not yet be pursued as part of this study. The following anchor item from the qualitative study shows the potential in this area:

> "I strongly believe that students adapt huge competences out of this situation, since it is so unique; and I do believe that as a future teacher you need to be flexible in every situation i.e. online seminars, e-learning, acquiring advanced media competences etc."

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Appendices

A – Deductive and Inductive Coding Categories

Deductive Coding Categories (Types of Online Interaction)	Category Definition	Inductive Coding Categories	Unrevised Anchor Examples
Learner-self Interaction	Learner-self interaction occurs within learners to help monitor and / or regulate their own learning. (Ally, 2011, p. 33)	• Freedom & independence • Time efficiency • Personal well-being	"I simply do not like to spend a lot of time in front of the screen and study in isolation. Therefore, it is often difficult for me to encourage myself to take on working again."
Learner-interface Interaction	Learner-interface interaction occurs between the student and different interaction media (Moodle, BBB, etc.) as well as related hardware to access the content and to interact with others. (Ally, 2011, p. 33)	• Tools • Infrastructure	"Often times it's hard to follow a lecturer because of technical difficulties. This disturbs the rhythm of speech and makes it difficult to stay on task."
Learner-content Interaction	Learner-content interaction describes the interaction between learner and the content as such as well as the didactic approach. (Ally, 2011, p. 33; see also Zheng et al, 2020)	• Task quality • Task quantity & workload • Objectives & assessment • Class organization • Methods	"Some seminars turn into lecture like meetings which make it very hard to stay focused. hard to make certain seminars as interactive as they would've been at the phs."
Learner-support Interaction	Learner-support interaction describes situations in which the learner is supported by (an)other learner(s), an instructor, or an expert when working through the content. (Ally, 2011, p. 33)	• Instructor-interaction • Peer interaction	"Professors offered lots of support – and some even extra hours which we could join if there were any questions or problems."
Learner-context Interaction	Learner-context interaction describes when learners are allowed to apply what they learn in real life so that they can contextualize the information. (Ally, 2011, p. 33)		"I strongly believe that students adapt huge competences out of this situation, since it is so unique; and I do believe that as a future teacher you need to be flexible in every situation i.e online seminars, e-learning, acquiring advanced media competences etc."

Note. The fifth category learner-context interaction was eliminated as a result of the convergent parallel analysis.

B – Intercoder Agreement

TAB. B1. *Kappa Values for both Coders at the 90 % Segment Level*

		Coder1		
		1	0	Σ
Coder 2	1	a = 270	b = 311	581
	0	c = 258	0	258
	Σ	528	311	839
Note	*P*(observed) = *Po* = a / (a + b + c) = 0.32 *P*(chance) = *Pc* = 1 / Number of codes = 1 / 5 = 0.20 κ = (*Po* - *Pc*) / (1 - *Pc*) = 0.15. If there is an unequal number of codes per segment or if only one code is to be evaluated: *P*(chance) = *Pc* = Number of codes / (Number of codes + 1)² = 0.14 κ = (*Po* - *Pc*) / (1 - *Pc*) = 0.21.			

TAB. B2. *Kappa Values for both Coders at the 10 % Segment Level*

		Coder1		
		1	0	Σ
Coder 2	1	a = 505	b = 191	696
	0	c = 143	0	143
	Σ	648	191	839
Note	*P*(observed) = *Po* = a / (a + b + c) = 0.60 *P*(chance) = *Pc* = 1 / Number of codes = 1 / 5 = 0.20 κ = (*Po* - *Pc*) / (1 - *Pc*) = 0.15. If there is an unequal number of codes per segment or if only one code is to be evaluated: *P*(chance) = *Pc* = Number of codes / (Number of codes + 1)² = 0.14 κ = (*Po* - *Pc*) / (1 - *Pc*) = 0.54.			