Social Interaction Data-sets in the Age of Covid-19: a Case Study on Digital Commensality

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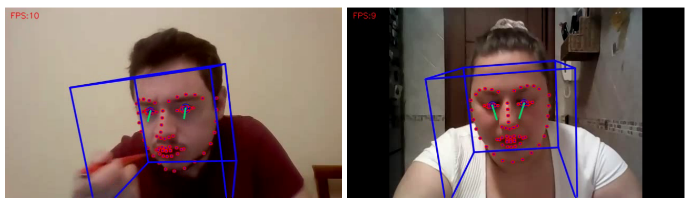

Figure 1: Two frames from the Digital Commensality data-set, with face tracking.

ABSTRACT

Research focusing on social interaction often leverages data-sets, allowing annotation, analysis, and modeling of social behavior. When it comes to commensality, researchers have started working on computational models of food and eating-related activities recognition. The growing research area known as Digital Commensality, has focused on meals shared online, for instance, through videochat. However, to investigate this topic, traditional data-sets recorded in laboratory settings may not be the best option in terms of ecological validity. Covid-19 restrictions and lock-downs have increased in online gatherings, with many people becoming used to the idea of sharing meals online. Following this trend, we propose the concept of collecting data by recording online interactions and discuss the challenges related to this methodology. We illustrate our approach in creating the first Digital Commensality data-set, containing recordings of food-related social interactions collected online during the Covid-19 outbreak.

CCS CONCEPTS

• **Human-centered computing** → *Human computer interaction (HCI)*; *Empirical studies in HCI*; • **Applied computing** → Computers in other domains.

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KEYWORDS

data-sets, commensality, social signal processing, activity recognition, covid-19

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1 INTRODUCTION

There is a growing research interest in computational approaches to deal with everyday social activities [2, 15, 21, 23]. Such methods often leverage data-sets, made-up, for instance, videos, motion-captured data, audio, and images portraying such activities in both laboratory and ecological settings. Food-related social activities have recently started drawing the attention of computer scientists, especially in HCI and Computer Vision. [19] use the term *Computational Commensality* to describe computational models of commensality, for instance, aimed at automatic recognition and synthesis of eating activities or at modeling social interaction around meals. Examples of applications include: 1) Artificial Commensal Companions [12], i.e., embodied agents (e.g., social robots) that can provide multimodal interactions with humans as they eat; 2) the detection of commensal activities such as chewing, speaking, and food intake using audiovisual data [4, 22]. In the same line, *Digital Commensality* [24] focuses on "the role of technology in inhibiting/facilitating the more pleasurable social aspects of dining", including sharing meals online through video-conferencing software. Studies focusing on this peculiar form of commensality have shown how, despite not always being satisfactory, Digital

Commensality can still provide the same sense of belonging and togetherness that sharing meals provides [5]. Nonetheless, recordings in laboratory settings or controlled environments might not be the best option to address Digital Commensality, especially concerning ecological validity. We speculate that the same also applies to other social behaviors occurring online, such as work meetings, gatherings, etc. In this paper, we present the creation of a data-set in which we recorded online meals through a video-conferencing app. We discuss the participants' Digital Commensality experience, assessed through the Digital Commensality Questionnaire [5] and through video-recorded nonverbal behaviors. We aim to show how remote data collection can be a feasible option for investigating online social interactions and building models for computational (e.g., recognition/detection).

2 RELATED WORK

2.1 Social interaction data-sets

Audiovisual data-sets are commonly used to study social interaction. They gather verbal and non-verbal behavior, affording a thorough investigation of social signals, often including annotations of specific research questions and points of interest. Moreover, data-set may also be accompanied by questionnaires filled out by the participants portrayed in the videos, thus enriching the content with measures of their experience, opinion, emotional state, etc. Such data-sets are often used to create audio- and/or video-based detection/recognition (e.g., leadership detection such as in [2]) and synthesis (e.g., interaction models for embodied agents [20]). For example, the MUMBAI data-set [8] contains four-player board game sessions recorded via multiple cameras, resulting in 46 hours of material. The data-set is annotated with emotional labels for all sessions. Also, it contains personality and game experience questionnaires filled out by the participants. Similarly, the GAME-ON data-set [17], aimed at the study of group cohesion, is made up of videos and motion capture recordings of groups participating in an escape game. The participants filled out questionnaires before, during, and after the game, assessing team cohesion and the efficacy of their co-players. To the best of our knowledge, no data-set focusing specifically on commensal activities has been proposed. Hossain et al. [14] collected data of triads consuming meals in a laboratory setting. However, their work aimed at the automated detection of individual chews and bites. Nonetheless, one could also leverage their data to study the social dynamics of commensal partners. Other available data-sets mainly focus on single-person activity, e.g., food preparation [18], or acoustic properties of sounds from people consuming different food [13].

2.2 Data-sets in the age of Covid-19

With Covid-19 forcing people to stay home, a shift has been observed across research domains, with researchers moving their studies online when possible. In [25], a survey illustrates this shift in developmental research, pointing out advantages and shortcomings. Similarly, [11] addresses online studies in Psychology, raising points that, we believe, could also apply to data-sets-based research. For instance, they mention how online studies could lead to noisier data and higher drop-out rates, but, at the same time, they make it possible to collect more extensive and quicker data amounts and ensure higher anonymity. [7] illustrates a study in which a data-set containing conference videos was used to validate their semantic segmentation approach. Moving on to social interaction studies, [16] describes deception detection in group video conversations and points out the importance of considering such a kind of interaction, as video calls are becoming increasingly common after the Covid-19 hit. [3] recorded, through video-calls, conversations between children and their caregivers to investigate gaze, gesture, and facial expressions. Similarly, [26] created a corpus of parent-children speech interactions fully collected online and advocates for such an approach to overcome the limitations caused by lock-down policies. The following section illustrates the first Digital Commensality data collection in line with this trend.

3 DIGITAL COMMENSALITY STUDY

Our study, carried out in May 2021, aimed at investigating Digital Commensality by looking at remotely shared meals, through videos and questionnaires, as opposed to previous work by [5] only including questionnaires measuring the attitude towards such a kind of experience.

3.1 Recordings

We recruited participants among the experimenters' friends and relatives. A total of 22 volunteers took part in the recordings. 12 were females and 10 males. Out of 22 participants, 16 were between 18 and 24 years old, 3 between 25 and 29, and 3 were over 55. Upon agreeing to take part in the study with a friend or family member, participants were sent an email with their unique ID, the link to the first questionnaire (see Section 3.2), the instructions for setting up their table with a computer, as illustrated in Figures 2 and 1. Also, they were asked to fill out a consent form before taking part in the experiment and the link to an online video call with the experimenter.

As they logged in, the experimenter greeted them by informing them about the procedure and the possibility of dropping out at any time. After checking the table and computer setup, the experimenter told participants they could start eating and then muted his mic and turned off his webcam. We gave no constraints regarding meal duration: we invited participants to eat for as long as needed and signal to the experimenter when their meal was over. When that happened, the experimenter would join the call again to answer participants' questions and to ask them to complete the final questionnaire (see Section 3.2).

Figure 2: The data collection technical setup.

Figures 1 and 2 display the experimental setup. A person is sitting in front of a computer, so that their head and part of upper body are visible through the webcam.

3.2 Questionnaires

Both of the questionnaires we administered to the participants were in Italian and were anonymous.

3.2.1 Before the recordings. Before the shared meal, we asked participants to complete a form collecting demographic information (age range and gender), type of relationship with the co-diner (friends, very close friends, best friends), and the number of daily video-chats. Moreover, we asked them to respond to a questionnaire assessing their attitudes towards video-chats. To this aim, items from the Computer Mediated Communication Questionnaire [27] were selected and translated (see Table 1).

Question	Please indicate how much you agree or disagree with the following statement:
*CMCQ*1	CMC allows me to perform social interactions
*CMCQ*2	CMC allows me to carry on informal conversations
*CMCQ*3	I am comfortable using CMC to communicate with a single individual or multiple people
*CMCQ*4	It is difficult to express what I want to communicate through CMC
*CMCQ*5	CMC communication becomes easier as I become more experienced in its use
*CMCQ*6	CMC allows me to build more caring social relationships with others
*CMCQ*7	CMC permits the building of trust relationships

Table 1: Computer Mediated Communication Questionnaire

3.2.2 After the recordings. We asked participants to complete another questionnaire to assess the Digital Commensality experience when the meal was over. To do so, participants responded to the Digital Commensality Questionnaire (DCQ) [5], which we created to investigate the effects of social interaction on the eating experience in terms of food liking, sense of belonging, feelings of loneliness, and boredom. Table 2 illustrates the DCQ items used in this study. The questionnaire contained two extra items we added for this study (*DCQ*7 ad *DCQ*8). In addition to this, we asked participants to indicate possible negative aspects of the experience among the list of options: network problems, hearing the noise of the commensal chewing, seeing the commensal chewing, being watched while chewing, being unable to share smell or taste with the other person, communication problems (e.g., talking at the same time), personal dislike towards video-calls, none. Lastly, through an open-ended question, participants were asked to describe the best possible technology for digital commensality they could envision.

4 PRELIMINARY RESULTS

Besides further investigating Digital Commensality, our study also aimed to explore the feasibility of conducting such a study remotely. This section illustrates the output of our data collection in terms of recordings, questionnaires, facial expressions, and ideas for future annotation.

Question	Please indicate how much you agree or disagree with statements Q1-Q6 and provide a rating to Q7-Q8:
*DCQ*1	Eating or drinking with others online helps me feel closer to them
*DCQ*2	Eating or drinking with others online makes our meet-up more interesting
*DCQ*3	Eating or drinking with others online makes our meet-up more fun
*DCQ*4	Eating or drinking with others online helps me feel as if we were actually together
*DCQ*5	Eating or drinking with others online helps me feel less alone
*DCQ*6	Eating or drinking with someone else online makes me appreciate my food more
*DCQ*7	Overall, how would you rate the digital commensality experience?
*DCQ*8	Compared with eating in person with the same person, how would you rate your digital commensality experience?

Table 2: Digital Commensality Questionnaire items. During the experiment Italian version of the questionnaire was used.

4.1 Video recordings

In total, we recorded 22 participants. The total length of recordings is 3 hours and 37 minutes, with a video resolution of 640x360 pixels at 25 fps. The average duration of a single meal is 10 minutes and 50 seconds (with the shortest meal lasting 5 minutes and 18 seconds and the longest one lasting 16 minutes and 17 seconds). We also validated the quality of the videos by processing them with state-of-the-art face tracking software (i.e., OpenFace [1], see Figure 1). Results are really good for most participants, with a 4% frame drop, on average. Only for one participant, this result was much lower (38% of dropped frames). By reviewing this video, we noticed that the participant's webcam was slightly above his head and how he tended to tilt his head forward to eat the food (instead of raising his fork), resulting in his face not being visible during food intake. It will be crucial to carefully check the camera set up to avoid this issue in future recordings.

4.2 Questionnaires data

Here we show the results from the questionnaires. Table 3 reports the mean score and mode for each 5-points Likert scale item of the Computer Mediated Communication questionnaire and the Digital Commensality Questionnaire.

Question	Mean (s.d.)	Mode		Question	Mean (s.d.)	Mode
CMCQ1	4.043 (.767)	4		DCQ1	4.136 (.990)	5
CMCQ2	3.956 (.877)	4		DCQ2	3.727 (1.120)	4
CMCQ3	3.478 (1.122)	4		DCQ3	3.772 (1.195)	4
CMCQ4	2.695 (.973)	3		DCQ4	3.590 (.908)	4
CMCQ5	4.130 (.757)	4		DCQ5	4.181 (.852)	5
CMCQ6	3.695 (.875)	3		DCQ6	3.227 (1.306)	4
CMCQ7	3.347 (1.112)	3		DCQ7	3.863 (0.774)	4
				DCQ8	2.636 (0.847)	3

Table 3: Mean score and mode for each item of the Computer Mediated Communication Questionnaire (left) and Digital Commensality Questionnaire (right).

We used the CMC Questionnaire to understand our experimental sample better as, we believe, familiarity with online meetings and, more generally, with CMC might affect the results. We suggest remote studies should include such measures. In our sample, participants reported, on average, being at ease with using computers to communicate.

The DCQ questionnaire is meant to assess participants' experience of the remote meal and the effect of sharing a meal with their commensal on social interaction. Overall, our results show participants had a positive experience and enjoyed their meal. Furthermore, their responses map research on Digital Commensality [5], [6]. These scores suggest our approach to be a viable option for investigating Digital Commensality. We speculate that one could adopt the same methodology to investigate other forms of online social interaction.

4.2.1 Correlation between facial expression and questionnaires. We computed the correlation between the DCQ items and the average and max values of the Facial Action Units [10] of the participants, automatically extracted using OpenFace (see Section 4.1), to check whether the nonverbal behaviors captured in the videos may reveal reported internal states and attitudes of the participants. More specifically, we focused on the participants' responses to $DCQ3$ ("Eating or drinking with others online makes our meet-up more fun") and $DCQ7$ ("Overall, how would you rate the digital commensality experience?"), as they could reveal their affective states (i.e., whether the experience was positive or negative). Then, we considered the average and max values of $AU4$ (Brow Lowerer) and $AU6$ (Cheek Raiser) computed on the whole video recording. We focused on these two Action Units, as $AU4$ is often associated with negative affective states, such as anger[9], whereas $AU6$ is considered an indicator of felt "true" enjoyment ("Duchenne" smile [9]). Results show that $AU4$ is negatively correlated (average -0.26, max -0.34) while $AU6$ is positively correlated (average 0.33, max 0.42) with both $DCQ3$ and $DCQ7$. This result shows that it could be possible to automatically detect the participants' affective states of an online shared meal by analyzing their nonverbal behaviors.

4.2.2 Open questions. When asked to choose the main downsides of their Digital Commensality experience, most participants indicated the impossibility of sharing food and smell and the network problems, such as delays and overlaps. When it comes to suggestions for future Digital Commensality, all responses show the need for the illusion of being together, sharing the same physical space. For instance, participant 18 suggested how a camera from the top would give the possibility to see the other person's whole table setting, thus sharing more information on their meal. Participants 5, 13, 14, 16, and 17 said they wished for the possibility of conveying sensory information, such as smell, taste, or touch, to create the illusion of being together. Overall, these suggestions match the results of previous Digital Commensality studies, highlighting that the need for belonging and togetherness is the main reason for eating together online [5],[6]. To use the words of participant 6: *future technologies should remove all the barriers that remind you of being in two different places*. Responses to the open questions allowed us to study the participants' opinions and attitudes toward Digital Commensality. Although they were allowed to leave the form blank, none of them did it, confirming the fact that anonymous yet open questions foster free sharing of opinions.

4.3 Annotation

We believe that our data-set offers multiple annotation possibilities, as it is rich in social cues, both verbal and non-verbal. In our view, one could fruitfully exploit remotely collected videos for this purpose. For instance, we propose to annotate a set of most significant commensal activities. As such activities have at least two primary goals, i.e., food consumption and social interaction, annotation also needs to include the related activities. For example, food in-taking, drinking, and chewing when looking at food consumption; speaking, smiling, laughing, and gazing at something when addressing social interaction. More interestingly, they may be performed at the same time by the same person (e.g., speaking and eating) as well as the same activity performed by two or more persons may overlap (e.g., both are talking or eating at the same time). The annotation of social signals, e.g., smiling, speaking, may help learn about the social bonds and relations (see, e.g., [15]).

5 DISCUSSION AND FUTURE WORK

In this paper, we proposed the idea of investigating online shared meals through video-recorded social interactions. To do so, we presented a new data collection protocol and some ideas for future annotation. To validate our approach, we used the Digital Commensality Questionnaire, a set of open-ended questions, and a preliminary analysis of facial expressions. Results are promising for the video recording quality, measured participants' experience, and overall richness of information. We believe that our approach would be a viable option for investigating remotely shared meals. Nevertheless, the methodology we propose holds some shortcomings, in line with those reported about Zoom-based data collection [25]. More specifically, the lack of control in the experimental setting, allowing participants to freely and ecologically interact, came with noise in the collected data and minor loss of information. In our data, one main limitation lies in the resolution of videos (see Section 4.1). However, this is the typical resolution of standard video-conference tools for the synchronized view. In addition to this, the webcam was sometimes too close to the participants, preventing us from capturing, e.g., upper body movements, plates, etc. We preferred not to position the participant's webcam too far (to capture a broader view of what the participant is doing), as it could result in the video of the commensal partner being too small, preventing a natural interaction. We could avoid these issues by replacing the standard devices we used (e.g., consumer-level laptops) with professional cameras that we can adjust according to the participant's needs or specific research requirements. Participants often chatted about personal topics while eating. Whereas that suggests that participants felt at ease while interacting and eating in front of a webcam, it may result in an ethical issue regarding data sharing and processing. So, even though participants signed a consent form allowing us to use the audiovisual recordings for research purposes, we preferred not to include audio in our data-set. Nevertheless, our approach allowed us to collect rich information on remote dinners during a time in which, in Italy, recording meal interactions in physically shared places would not have been possible due to Covid-19 regulations. Through our approach, we were able to create the first Digital Commensality data-set that, we hope, could be leveraged for different purposes: from developing novel computational models of commensality to gaining a deeper understanding of remote social interactions.

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