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How can technologies help disclose new insights into collective behaviors?

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Abstract
Technologies increasingly shape our lives but also how research is done. Nowadays, we can use complex technological tools to examine unexplored research territories. In this regard, we focus in this work on collective experiments involving direct social interactions without systematic intermediaries. The contribution of this paper is twofold. First, we remark on the importance of studying collective processes, which are still scarcely considered in the existing experimental literature in economics, and the multimodal use of technological tools to study those processes in a controlled environment. Second, we bring a greater focus on the tools themselves, their characteristics, and their wearability. With this, we highlight the importance of the collaboration of economics in multidisciplinary projects, e.g., with psychology or engineering. We also highlight the potential of collective experiments and the importance of integrating technologies into the experimental methodology, at the same time acknowledging the existing barriers and limitations in studying such complex phenomena.

JEL Classification: C92; D7; D91; O31

Keywords
Collective experiments — Multidisciplinarity — Technologies — Multimodality

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Introduction

We form part of a world every time becoming more globalized and connected. Hence, social interactions and collective activities are fundamental aspects of our societies, shaping our daily lives in numerous ways. In this sense, we are part of a shared environment where there are two-directional interactions in which society affects us, and our behavior impacts others. To better understand how these complex and multidimensional processes operate, the study of collective phenomena has great importance. Experimental and behavioral economics have tremendous potential in this regard because they offer an adequate tool for comprehending the interactions of the subjects' behaviors in collective processes. Indeed, by using the experimental methodology, we are able to observe specific mechanisms or processes under a controlled environment [Friedman and Sunder, 1994; Jacquemet and L'Haridon, 2018]. Furthermore, this methodology allows an understanding of how and why the interaction takes place and which are the repercussions on the collective process. Due to the intrinsic complexity of collective processes, the experimental approach represents the most promising methodology for studying the core collective mechanisms at stake.

This paper focuses on studying collective experiments differently from the traditional literature, aiming to be closer to real-life scenarios and corresponding to the following definition of "*experiments involving subjects in direct social interactions without any kind of systematic intermediary.*" In these collective experiments, we observe direct interactions among subjects, and thanks to this, we can better understand collective processes in different environments, such as competition or cooperation. Introducing this specific type of experiment where there is no systematic intermediary between subjects implies that the condition of anonymity is waived. However, this condition is considered a key requirement in experimental economics. We do not deny the importance of it. Instead, we offer to control it in the protocols and assist in implementing technological tools. Nevertheless, the main contribution to the literature is to explore situations where systemic intermediaries are removed to enrich the experimental approach and provide the possibility of studying social interactions closer to reality, such as in a bargaining context or enterprise teamwork.

Nonetheless, this also complicates the collection of such data, which raises a natural convergence to other fields' methodology with more focus on studying the processes instead of the pure decision. For this reason, another contribution of this work is also to list the tools that can improve the understanding of collective processes, some used in other disciplines from which economists could draw on their expertise.

Furthermore, the untiring technological development brings technologies with enormous potential to disentangle the dynamics in the collective processes. Those technologies offer the possibility to explore different dimensions of economic questions, such as the group outcome, which is misregarded by the literature in experimental economics because it was not achievable to study it under a controlled environment before.

The same happened with the laboratory experiments in the 70s.

The main goal of this paper is then to explore what perspectives experimentalists can envision for future research on collective processes by associating those new sources of data with adequate technologies and methodologies. For this reason, we would like to stress the importance of a multidisciplinary and multimodal approach to the collection and analysis of different sources of data in experimental protocols dedicated to collective processes.

The remainder of the paper is organized as follows. Section 2 focuses on collective experiments in the literature and their limitations. Section 3 describes the available technologies that have the potential to improve the study of collective processes in social sciences. This section also includes the specific example of the *Social Interactions Lab* (SIL), an experimental laboratory conceived for the study of collective processes. Finally, Section 4 focuses on recommendations to incorporate those technologies in their studies, the potential of the information provided by those tools, and their limitations.

Collective behavior in experiments

To gain a comprehensive understanding of new technologies and their implications in terms of collective experiments, it is essential first to define the contextual framework in which they operate. This includes characterizing what qualifies as a collective experiment, reviewing existing literature on such protocols, and presenting the existing limitations.

Literature

The literature in experimental economics has mainly devoted its attention to individual decision-making also in the presence of strategic choices and group interaction [Kagel and Roth, 1995]. As for the latter, there exist a plethora of experimental studies on group behavior looking at the consequences of the decisions of others on the subject's gain in different topics, such as on cooperation [Andreoni, 1995; Fischbacher et al., 2001], bargaining [Cason and Friedman, 1997] or creativity [Attanasi et al., 2021, 2019; Charness and Grieco, 2019, 2023]. However, in the overwhelming majority of these studies, the focus is about individual characteristics (e.g., altruism in a public good game) and/or the collective outcome (e.g., efficiency), by disregarding the interaction process leading to that outcome. This is because usually an intermediary rules the experiments and generally it takes place through a computer interface or in a pencil-and-paper form. Therefore, direct interaction among experimental subjects is not possible by construction.

Thus, the current literature has paid little if any attention to direct interaction without a systemic intermediary, and so on the process itself beyond the collective outcome. Nevertheless, the literature on experimental economics does not just consider the traditional laboratory experiments. Also, it has increasingly grown in prominence in field experiments. The main potential of field experiments is that they offer two factors that improve the external validity: the representativeness of the environment and the sampled population [List, 2007]. Therefore, experimentalist faces a trade-off between control of the experimental setting and external factors (internal validity) and the proximity to a real-life setting (ecological validity[1]).

Definition of a collective experiment

Social interactions greatly influence our behavior and choices, making their study challenging due to the diverse range of individuals involved and the complex environmental factors at play. In order to better understand this phenomenon, one possible approach is experimentation. As exposed in the previous subsection, laboratory experiments allow for observing behaviors in a highly controlled environment, and field experiments offer the possibility to have a more natural representation of the event in terms of environment and sample. Thus, we might question what limits laboratory experiments in realizing their potential to enhance their ecological validity when studying collective processes. We assume that this limit exists because of the fundamental principle of anonymity in experiments.

In the outside world, social interactions occur between individuals who can communicate and identify with each other without systematic isolation, such as buying in the market or meeting at work. Through collective experiments, one might address this dimension not exploited in economics, in order to better understand direct social interactions' role in individuals' choices and the resulting collective outcomes. Nevertheless, one might still question the significance of removing intermediaries between subjects when studying collective processes. For instance, a computer interface is the most used in experimental economics. Hence, we need to question the subject's perception of an interaction with one or more other subjects when such an intermediary is (not) involved. As simple as it may seem, does it matter what is on the other side of the computer? Would face-to-face interactions alter subjects' behaviors or choices in a laboratory experiment?

We hypothesize that the answer to these questions is yes. It alters behaviors because of the fact that having an interface between subjects (such as computer-based experiments) creates what we define as an "*intermediate interpretative layer*." In the case of interactions without intermediaries, subjects are able to gather information on their interlocutors from both direct and indirect sources due to their physical proximity. When an intermediary is added, subjects face an information gap. One could argue that this would imply less information to process, but it also represents an additional cost for subjects who need to fill those gaps according to their beliefs or expectations. Ambiguity emerges and creates a cognitive load for the subject and possible misinterpretations. Thus, we assume that removing intermediaries between subjects while studying collective processes could help preserve ecological validity

[1] Derived from the psychological field and defined as "*the relation between real-world phenomena and the investigation of these phenomena in experimental contexts*" (p.420) [Schmuckler, 2001].

and also provide richer insights (more information) into the collective process.

Friedman and Sunder [1994] argue that a discipline's theoretical context determines its ability to conduct experiments rather than the discipline being inherently experimental or non-experimental. Given the evident lack of references on collective experiments, and in light of the observation made by Friedman and Sunder [1994], it is plausible to hypothesize that the use of collective experiments was hampered by the inadequacy of the techniques available to provide the necessary control. Furthermore, direct social interactions lead to loss of anonymity which is relevant for external and ecological validity.

Therefore, the potential technologies should offer relevant tools for studying and controlling collective interactions with no systematic intermediary. In the following section, we will list and describe those technologies. Some of them are already used by other disciplines, such as psychology, management, or engineering, which remark on the importance of multidisciplinarity in adressing this issue and, in general, in experimental methods. To sum up, the objective is to combine traditional experimental methods in the laboratory with technologies and tools so as to better understand the complex phenomenon of collective processes. The new technologies should provide controls for the heterogeneity of the individuals in their interactions and the role of different contexts and environments in these two-way relationships.

Technologies

Based on previous considerations, exploring the available and emerging technologies and tools that can enhance the analysis of collective processes in a controlled environment seems crucial. This section will divide the relevant tools to understand collective processes into categories tailored to specific interests, namely subjects' **(a) emotional states** and their **(b) motion**, emphasizing the critical elements and characteristics and comparing them. The information is summed up in Appendix A. While technologies for measuring and analyzing emotional states are currently spreading in experimental economics laboratory, we claim that subjects' motion during economic experiments is still underestimated and, therefore, under-analyzed.

(a) Emotion recognition

Interactions between individuals naturally lead to communication, which can take the form of verbal or non-verbal signals. Incorporating both aspects is essential to comprehend fully any collective process and distinguish the different mechanisms behind them. In the case of collective experiments, both verbal and non-verbal communication signals can be used to analyze the subjects' emotions. Indeed, emotions[2] play a significant role in influencing both the physiological and psychological state of individuals, and the complex interplay between these factors makes emotion recognition a challenging task. The related tools can also be distinguished based on their verbal or non-verbal signals and their biometric or non-biometric nature[3]. On characterizing emotions, we follow the circumplex model of

Body language

Three main non-contact[4] techniques in the context of emotion recognition through body language are Facial Expressions (FE), Body Posture (BP), and Gesture Analysis (GA) [Glowinski et al., 2011; Kleinsmith and Bianchi-Berthouze, 2013]. These physical external signals for valence and arousal, distinct from internal physiological signals discussed later, can be analyzed using automated tools. Advancements in body language analysis technology enable faster and cost-effective tracking through video recordings and algorithms, replacing manual coding with more accurate and objective automated recognition of movements that do not require additional expertise from researchers except possible algorithmic competencies.

Brain activity

By examining brain activity, researchers gain insights into the underlying processes associated with emotional arousal and valence. The main technique to observe brain activity is electroencephalography (EEG), a contact sensor allowing researchers to capture the electrical activity of subjects' brains while facing different stimuli. The resulting waves and their frequencies allow researchers to assess subjects' EEG-responses to experimental stimuli [see, e.g.,Coricelli et al., 2019].

Skin conductance and temperature

Emotional arousal can also be detected by capturing variations in Skin Conductance (SC) and Temperature (SKT), two contact tools. First, SC [5] can be defined as the "*continuous measurement of electrical parameters of human skin*" (p.9) [Dzedzickis et al., 2020]. The changes in subjects' sweating provide valuable insights into the temporal aspects and frequency of emotional responses. Then, SKT provides valuable information about the autonomic regulation of blood flow to the skin that leads to changes in skin temperature.

Heart rate variability

Heart Rate Variability (HVR) can be defined as the variation in time intervals between successive heartbeats. Here, we focus on two main contact tools to assess HVR [Egger et al.,

[2] Defined as "*a 'shaking' of the organism as a response to a particular stimulus (person, situation or event), which is generalized and occupies the person as a whole*" (p.807) [Feidakis et al., 2011].

[3] Experimentalists can use biometric methods and affective computing, defined as a "*research area that studies and develops systems to sense the emotional state of a user (using sensors) and process them using computer systems to recognize the emotions*" (p.1) (**?**) to observe and measure bodily expressions.

[4] Contact sensors or tools refer to devices that require direct connection to the subject's body or skin to obtain data or measurements.

[5] Also called Galvanic Skin Response (GSR) or Electrodermal Activity (EDA).

2019; Sayed Ismail et al., 2022]. On the one hand, Electrocardiography (ECG) is based on the electrical activity of the heart, and on the other hand, Photoplethysmography (PPG or rPPG for remote application) is based on Blood Volume Pressure (BVP). Both represent two viable solutions to assess HRV and the subjects' emotional arousal.

Respiration rate

The Respiration Rate Analysis (RR) provides respiratory data through thoracic activity, shedding light on subjects' emotional states. RR allows researchers to observe subjects' emotional states, but many measurement techniques exist [Dzedzickis et al., 2020]. First, we can distinguish two main types of non-contact tools: the video-based detection of body movements and signals related to subjects' respiration (displacement of reference point) and on the other hand, the use of thermal cameras to detect temperature fluctuations. Second, as a contact sensor, RR can be provided by Respiratory Inductive Plethysmography, which measures the chest and abdominal wall movement.

Verbal communication

By capturing and analyzing the verbal exchanges among subjects, researchers can gain valuable insights into the form and content of subjects' interactions. This leads to a distinction between Speech Recognition (SR) and Voice Recognition (VR). The former is defined as a semantic analysis of exchanges, while the latter focuses on the acoustic aspect of these exchanges [Egger et al., 2019]. Either on the content or the form, it becomes necessary for researchers to gain knowledge of some analysis techniques, among which the quantitative approach of Natural Language Processing or the qualitative approach of Discourse Analysis through coding. From a practical point of view, the choice of microphone type is crucial, as it affects the capture of both voice lines and the surrounding environment. While an ambient microphone provides a means of control, it offers lower quality for analyzing verbal interactions than individual microphones.

(b) Motion detection

By allowing the motion of subjects into an experimental setting, the researcher introduces an additional dynamic dimension that needs to be controlled by an extensive knowledge of the subjects' positions and evolving trajectories. At the individual and collective levels, analyzing the subjects' motion in the laboratory enables a deeper understanding of their impact on the experiment's outcome and how stimuli can also impact those shifts. While the use of human coding is possible, the use of technological tools allows for more accurate data collection. Appendix A provides additional information on two main tools that can be profitable for researchers to understand subjects' motion: subject-tracking devices (non-contact) and inertia sensors (contact). If such tools make it possible to visualize and map interactions between subjects, they also make it possible to quantify these interactions, understand their dynamics, and identify patterns, roles, or other phenomena resulting from them, e.g., knowledge flows, social contagion, or preferential attachment. The resulting analysis requires additional expertise in mainly social-network analysis. Moreover, those technologies can seamlessly integrate with video and audio systems, enabling researchers to disentangle ambiguous situations. For instance, in scenarios where two subjects are in close proximity, the combination of tracking data with video footage and audio recordings can determine if they are facing each other, engaged in conversation, or simply back-to-back.

In collective experiments involving the mobility of subjects, researchers need to consider using suitable sensors that are minimally intrusive and allow for movements. **Wearable devices** – both for detecting subjects' motion and, in principle, for emotion recognition – would allow researchers to observe phenomena in settings closer to real-life environments and to run experiments with stronger ecological validity. While static devices are commonly employed in traditional laboratory settings, there has been a recent and ongoing development of non-intrusive and wireless tools designed to facilitate accurate measurements when dealing with mobile subjects. These innovative tools aim to collect reliable and robust data in scenarios where subjects are in motion. Appendix A presents different examples for each tool, including smartphones and watches, flexible electronics, or even sensors integrated into fabrics. In our survey we have consciously discarded certain tools, such as Electromyography devices, that do not seem to be the most suitable for laboratory experiments in economics, due to lower practicality and the existence of sufficient alternatives. This does not prevent experimental economists from using them, and we even encourage the readers to question the implementation of these tools.

As an example of collective experimentation involving the mobility of subjects, the *Social Interactions Lab* (SIL) currently provides a controlled environment suitable for real-life phenomena based on the principle of (i) non-systematic intermediaries between subjects, (ii) the possibility of face-to-face interactions, and (iii) subjects' motion during the experiment. Located in Strasbourg (France), the SIL is an experimental room of more than 100m² and designed to allow researchers interested in collective processes to come and carry out their experiments in a space different from the more traditional offer of experimental economic laboratories.[6] While in economics the usual experimental rooms are composed of fixed stations separated by partitions in which each subject is installed totally isolated, this laboratory has been conceived to allow face-to-face interactions. Another key point in the design of the SIL is the modularity of the space. Indeed, the SIL's layout can be adjusted depending on the researchers' needs relative to furniture quantity, setting, and/or delimited areas [Maltese et al., 2023]. Appendix B describes one possible layout and the existing tools within the SIL: a subject-tracking device for motion detection and networks' analysis in group behavior, as

[6] A control room (experimenter room) is attached to the creativity room that gathers all the measurement tools that can be used in the various experiments.

well as video and audio systems to assess subjects' verbal and non-verbal (body language) communication.

Conclusion

The paper's objective is to demonstrate the importance of the combination of the experimental methodology and several technological tools to better understand the complex phenomenon of collective economic processes and to be able to improve the control of direct social interactions in a laboratory setting. While some of those technologies are already widely used in other fields, we acknowledge the importance of the interplay among different disciplines. For instance, the psychology literature has extensive contributions, methods, and tools focused on processes that should arise a natural collaboration based on common interests. Therefore, there is a strong necessity for multidisciplinarity to understand collective processes better. Surely, by integrating diverse perspectives, we can enhance our comprehension of the entire phenomenon, thus addressing critical issues in the economic sphere.

Consequently, three key aspects should be emphasized when conducting collective experiments in economics in the future: the collaboration of researchers from different disciplines, the rethinking of existing protocols, and the multimodal aspects of data collection. First, we must consider the previous knowledge of other domains regarding their theoretical models, methodology, and analysis for using the aforementioned tools in combination with traditional experimental economics. Hence, this can be essentially achieved by creating collaborations between researchers from different disciplines according to their own expertise. Indeed, most of the references supplied in this paper come from engineering or computer science journals because, in most cases, using those tools requires technical knowledge about them. Nonetheless, we acknowledge that communication (terminology, methodology criteria, and interests) and the willingness to be open to new approaches will play a keen role in the success of multidisciplinary projects.

Secondly, the experimental protocols require changes to adapt to collective experiments. On the one side, in the case of groups or teams, we need to observe several individuals for one data unit. This increases exponentially the number of participants needed, creating difficulty in terms of economic resources and the availability of a large number of subjects, compounded by the possible complexity of the measures derived from the technologies mentioned above (also in terms of data synchrony). On the other side, from an ethical point of view, those technological tools necessitate the acquisition of subjects' images, voices, or even physiological data. Hence subjects have to be informed and agree on this data collection, which also requires extended validation by the ethics committees. Especially with regard to biometric data, when analyzed by experts, some of them could detect a body malfunction or even a pathology, e.g., EEG. Do the researchers have a moral obligation to report potential medical or pathological issues? This is undoubtedly one main question that researchers will have to agree on, knowing that this type of technology is growing in interest.

Third, the data collection needs to be multimodal. To fully understand the ongoing processes, experimentalists must gather, combine and synchronize several tools. This multimodality of measurements ensures a more robust and trustful analysis of collective processes, enhancing scientific interpretations and contributions. By integrating a subjective (self-assessment) and objective (tools' measurements) approach to their data collection and ensuring the combination of several data sources and technologies, we believe that researchers will create new research avenues for the current experimental practice in economics.

To conclude, even though we detailed the existing concerns and limitations in order to study collective behaviors in economics, they are of tremendous potential and still not exploited in economics. Moreover, the technological tools listed in this paper can contribute to the economics literature in many ways, not just by looking at collective processes. The study of individual decision-making could also benefit from this new approach by providing new insights into the interaction of the subjects with their environment and how it shapes their behavior and decisions.

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Appendices

Appendix A

	Motion		Emotion recognition - Body language	
Tools	Subject-tracking devices	Inertial sensors (1)	Video-based facial expression recognition	Video-based Body Posture and Gestures recognition
Aim	Accurately and continuously monitor and capture the position, movement, or orientation of the subjects.	Capture accelerations or changes in the velocity of subjects to investigate movements, activity, and gestures.	Capture and define the emotional, communicative, and psychological aspects of facial expressions.	Capture and define the non-verbal movements and spatial interactions of individuals through the alignment of the body (posture) and expressive movements (gestures).
Focus features	Full body	Torso/Back, Hand/Wrist, Feet/Ankle	Head/Face	Full body
Possible human coding	Yes	Yes	Yes	Yes
Degree of unconsciousness for the subject	Low	Low	Low	Low
Garment-based devices	Headband *(Kim et al., 2008)*	Headband *(Kim et al., 2008)*, Wristband *(Gao et al., 2020)*, Shirt *(Rosso et al., 2010; Pourbemany et al., 2022)*	Not applicable	Not applicable
Accessory-based devices	Badge *(Lederman et al., 2018)*, Smartphones *(Thorpe et al., 2019)*	Watch (*Maurer et al., 2006*), Bracelet (*Malhi et al., 2012*)	Not applicable	Not applicable
Contact (2)	Non-contact	Both	Non-contact	Non-contact
External altering factors (3)	No specific factor	Vibration, shocks, or movement patterns.	Lighting, glasses, masks, cultural factors, occlusions.	Lighting, subjects' clothing, cluttered background, occlusions.
Two-dimensional emotion recognition	Not applicable	Not applicable	Valence; Arousal (*Egger et al., 2019*)	Valence; Arousal *(Glowinski et al., 2011; Kleinsmith and Bianchi-Berthouze, 2013)*

Figure 1. Wearable devices for Motion and Emotion recognition

(Cont.)	Emotion recognition - Brain activity	Emotion recognition - Skin conductance and temperature		Emotion recognition - Heart Rate Variability	
Tools	Electroencephalography	Galvanic Skin Response devices	Skin Temperature Measurement devices	Electrocardiography (4)	Photoplethysmography
Aim	Measure the electrical activity of the brain to gain insights into the underlying neural processes and their relationship to behavior and cognition.	Measure changes in skin conductance to provide valuable insights into the physiological aspects of emotional and psychological processes.	Measure the skin surface temperature to understand the impact of environmental and psychological factors on the body's thermal responses.	Measure the electrical activity of the heart to assess cardiac autonomic regulation and the effects of stimuli on the cardiovascular system.	Measure changes in blood volume and flow in the skin to understand the cardiovascular dynamics and their relationships with various physiological and psychological processes.
Focus features	Head/Face	Torso/Back, Hand/Wrist, Feet/Ankle	Torso/Back, Hand/Wrist	Torso/Back	Head/Face, Hand/Wrist
Possible human coding	No	No	No	No	No
Degree of unconsciousness for the subject	High	High	High	High	High
Garment-based devices	Cap *(Vargas et al., 2021)*	Scarf *(Guo et al., 2016)*, Wristband *(Gao et al., 2020)*	Wristband *(Gao et al., 2020)*	Shirt *(Rosso et al., 2010)*, Scarf *(Guo et al., 2016)*	Headband *(Kim et al., 2008)*, Pocket *(Teichmann et al., 2015)*
Accessory-based devices	Headpiece *(Ahn et al., 2019)*, Glasses *(Kosmyna et al., 2019)*	Bracelet *(Iadarola et al., 2021)*	Bracelet *(Malhi et al., 2012)*	Bracelet *(Malhi et al., 2012)*, Headpiece *(Ahn et al., 2019)*	Ring *(Asada et al., 2003)*, Wristband *(Yang et al., 2019)*
Contact	Contact	Contact	Contact	Contact	Both
External altering factors	Muscle artifacts (eye blinks or head movements), environmental noise, subjects' hair, and scalp condition.	Cleanness or natural dryness of the skin, temperature in the room, psychological factor prior the experiment.	Temperature in the room, type of clothing, subjects' age, gender, overall health.	Subjects' weight, alcohol consumption, environmental noise, or movements.	Lighting, movements, temperature.
Two-dimensional emotion recognition	Valence; Arousal *(Egger et al., 2019; Dzedzickis et al., 2020)*	Arousal *(Egger et. al, 2019, Dzedzickis, 2020)*	Arousal *(Egger et. al, 2019)*	Valence; Arousal *(Egger et al., 2019; Sayed Ismail et al. 2022)*	Valence; Arousal *(Egger et al., 2019; Sayed Ismail et al. 2022)*

(Cont.)	Emotion recognition - Respiration Rate			Emotion recognition - Verbal communication
Tools	Video-based respiratory movements recognition	Thermal cameras for respiratory movements recognition (5)	Respiratory inductive plethysmography	Audio-based devices for speech and voice recognition
Aim	Measure respiratory movements from external body movements or signals to identify changes in respiration rate, breathing depth, or breathing regularity associated with stress, anxiety, or emotional arousal.	Capture the thermal radiation emitted by objects and create images based on temperature variations to gain insights into respiratory function, respiratory disorders, and the effects of interventions on respiratory parameters.	Measure and analyze respiratory parameters and patterns to gain a comprehensive understanding of respiratory function and behavior.	Study verbal interactions, speech patterns, language processing, or communication dynamics by analyzing the content, quality, or characteristics of speech, including speech rate, tone, pitch, or speech errors.
Focus features	Full body	Full body	Torso/Back	Speech
Possible human coding	No	No	No	Yes
Degree of unconsciousness for the subject	High	High	High	Low
Garment-based devices	Not applicable	Not applicable	Shirt *(Rosso et al., 2010 ; Pourbemany et al., 2022)*	Shirt *(Rosso et al., 2010)*
Accessory-based devices	Not applicable	Not applicable	Belt *(Ramos-Garcia et al., 2017)*	Watch *(Maurer et al., 2006)*
Contact	Non-contact	Non-contact	Non-contact	Non-contact
External altering factors	Lighting, clothing, respiratory conditions, motion artifacts.	Ambient temperature, clothing, respiratory conditions, natural body heat variation.	Clothing, respiratory conditions, motion artifacts, environmental noise.	Background noises and recording environment, speech articulation and pronunciation.
Two-dimensional emotion recognition	Valence; Arousal *(Egger et al., 2019)*	Valence; Arousal *(Egger et al., 2019)*	Valence; Arousal *(Egger et al., 2019)*	Valence (6); Arousal *(Egger et al., 2019)*

(Cont.)

(1) Inertia sensors can also be considered for body language measurements.

(2) Contact if a direct contact with the skin is necessary.

(3) External factors do not take into considerations the technological issues that can occur, e.g., poor cameras or microphones quality or placement, weak signals emission or reception, missing data, or sensors misplacement.

(4) ECG can also be considered for RR.

(5) Thermal cameras can also be considered for SKT measurements.

(6) The efficacy of valence measures is still in debate in the literature, see *Wagner et al. (2023)*.

Appendix B

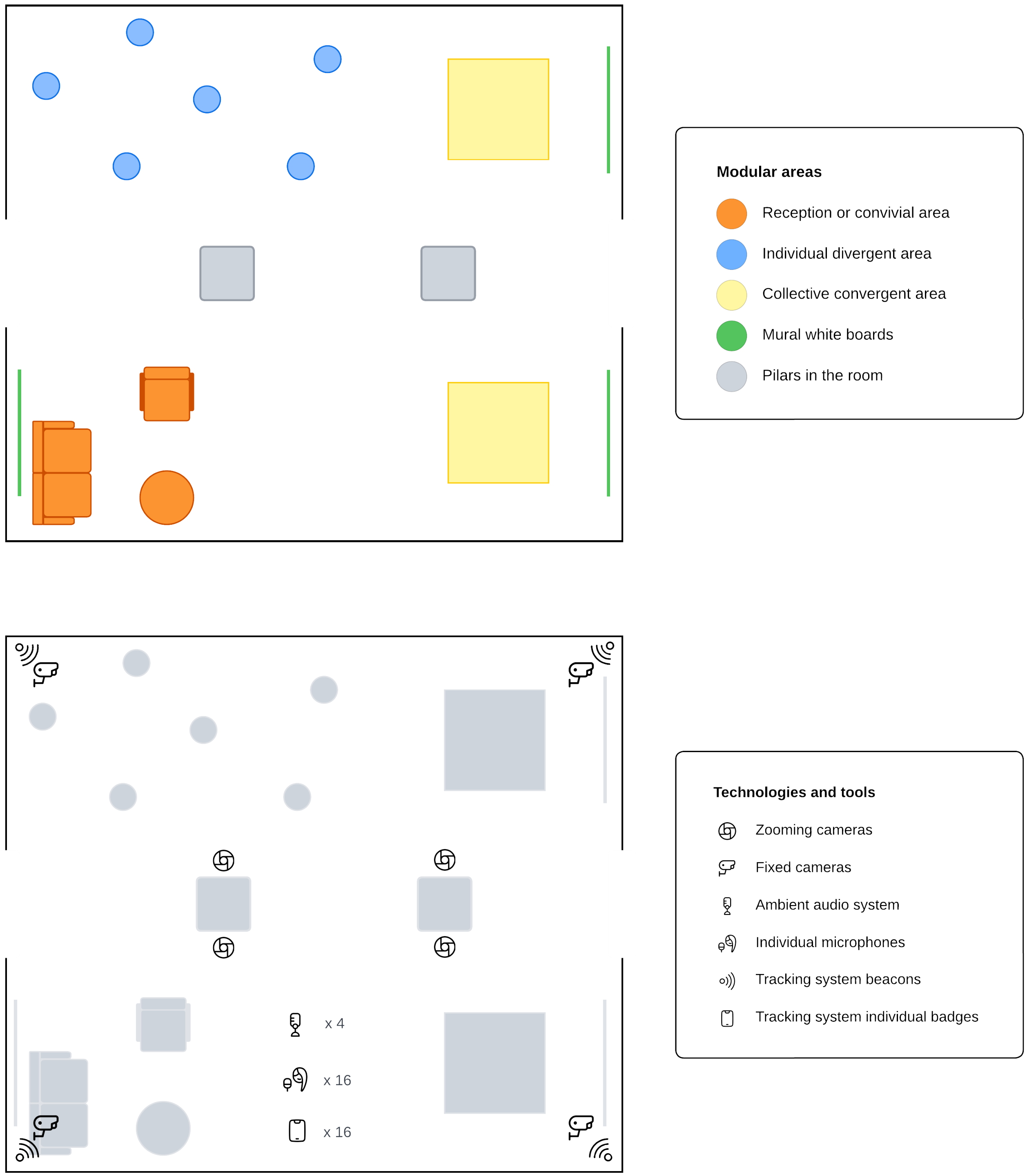

Figure 2. Layout and Measuring Tools Setting