Naturally Together: A Systematic Approach for Multi-User Interaction With Natural Interfaces

CARMEL SHAVITT*, Magic Lab, Industrial Engineering & Management, Ben Gurion University of the Negev, Israel
ANASTASIA KUZMINYKH*†, Faculty of Information, University of Toronto, Canada
ITAY RIDEL, Magic Lab, Industrial Engineering & Management, Ben Gurion University of the Negev, Israel
JESSICA R. CAUCHARD, Magic Lab, Industrial Engineering & Management, Ben Gurion University of the Negev, Israel

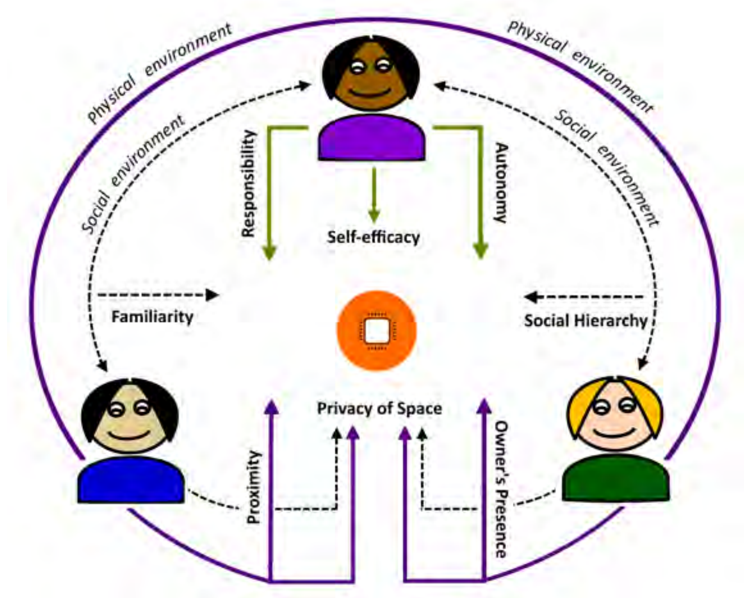

Fig. 1. Model of multi-user interaction built upon the environmental and user factors: Privacy of space, Owner's presence, Proximity, Familiarity between co-users, Social Hierarchy, User's sense of Responsibility, User's sense of Autonomy, and User's sense of Self-Efficacy. These factors affect interaction patterns with a natural interface system.

349

*Both authors contributed equally to this research.
†Also with Cheriton School of Computer Science, University of Waterloo.

Authors' addresses: Carmel Shavitt, carmelshavitt@gmail.com, Magic Lab, Industrial Engineering & Management, Ben Gurion University of the Negev, Be'er Sheva, Israel; Anastasia Kuzminykh, Faculty of Information, University of Toronto, Toronto, Ontario, Canada, anastasia.kuzminykh@utoronto.ca; Itay Ridel, ridel@post.bgu.ac.il, Magic Lab, Industrial Engineering & Management, Ben Gurion University of the Negev, Be'er Sheva, Israel; Jessica R. Cauchard, jcauchard@acm.org, Magic Lab, Industrial Engineering & Management, Ben Gurion University of the Negev, Be'er Sheva, Israel.

New technology is moving towards intuitive and natural interaction techniques that are increasingly embedded in human space (e.g., home and office environment) and aims to support multiple users, yet their interfaces do not cover it to the full. Imagine that you have a multi-user device, should it act differently in different situations, people, and group settings? Current Multi-User Interfaces address each of the users as an individual that works independently from others, and there is a lack of understanding of the mechanisms that impact shared usage of these products. Thus we have linked environmental (external) and user-centered (internal) factors to the way users interact with multi-user devices. We analyzed 124 papers that involve multi-user interfaces and created a classification model out of 8 factors. Both the model and factors were validated by a large-scale online study. Our model defines the factors affecting multi-user usage with a single device and leads to a decision on the most important ones in different situations. This paper is the first to identify these factors and to create a set of practical guidelines for designing Multi-User Interfaces.

CCS Concepts: • **Human-centered computing → HCI theory, concepts and models**; **Collaborative and social computing theory, concepts and paradigms**; *Empirical studies in HCI*; *Empirical studies in collaborative and social computing*.

Additional Key Words and Phrases: Multi-user interaction; Collaboration; Natural interfaces; Voice interfaces; Taxonomy; Review.

ACM Reference Format:
Carmel Shavitt, Anastasia Kuzminykh, Itay Ridel, and Jessica R. Cauchard. 2021. Naturally Together: A Systematic Approach for Multi-User Interaction With Natural Interfaces. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 349 (October 2021), 31 pages. https://doi.org/10.1145/3476090

1 INTRODUCTION

Alongside the growing ubiquity of technology, the systems design community faces an increasing need to learn how to appropriately support multi-user interactions, in particular, scenarios requiring simultaneous interactions between several people and a system. Multi-User Interactions (MUIs) differ from single-user scenarios, since they often require management and negotiations on input between co-user [77, 102, 111], especially when a device can handle limited number of simultaneous users. For example, interaction patterns of co-users can be shaped through turn-taking or through an "appointment" of a user responsible for input in a collaboration group [16]. Management and negotiation around interaction patterns, i.e. group decision making on who and how manipulates the device to achieve harmonic and mutually satisfying interactions, is guided by the situational factors [122], which highlights a particular importance of technologies' ability to understand social and environmental contexts to support proper multi-user interaction patterns [92]. However, while research actively investigates diverse application domains for multi-user interactions (e.g., smart homes [44, 119, 139, 146], collaborative digital surfaces [102, 113, 118, 123], collaborative writing [72, 134]); there is still no systematic understanding of the mechanisms that define multi-users interactions patterns [35].

This gap becomes particularly apparent as we move toward natural language communication (e.g., conversational agents [2] or robotic user interfaces [8, 23]), challenging the ability to appropriately generalize the results from previous research on multi-user interactions, which has been predominantly done on graphical interfaces. Specifically, the distinguishing characteristic of voice interfaces is the lack of physical token of control over the system, which would allow to explicitly manage inputs of multiple users and provide cues for organization of multi-user interaction space. Due to the absence of visual clues, affordances, and spatial organization, the use of natural language communication is associated with the decreased sense of control. For example,

2573-0142/2021/10-ART349 $15.00
https://doi.org/10.1145/3476090

current conversational technologies (e.g., Amazon Alexa, Google home) tend to be designed for a single user input, while they are actively expanding in home spaces, which are inherently multi-user [10]. As a result, when a situation prompts several people to interact with a conversational agent simultaneously, they either have to carefully negotiate turn-taking [43, 104, 106], or run into a danger of potentially overwriting another user's request or being ignored by the system [6]. Unsurprisingly, such interactions tend to result in unfulfilled requests and conflicts between co-users [43].

The systematic understanding of factors affecting multi-user interaction patterns would allow technology designers to identify the commonalities and differences in users' group input management between different types of systems, and adequately apply previously accumulated knowledge to the design of novel multi-user systems. Correspondingly, the goal of this paper is to develop a theoretical model of the relevant factors based on a systematic review of prior works on multi-user interactions, and to identify its fitness for voice interfaces as an example of natural language communication systems with no physical token of control. To develop this model, we first present an extensive review of the literature on multi-user interactions with diverse technologies and identify factors affecting multi-user interaction patterns. These factors were organized into a classification which identifies them as either environmental or user-centered (Figure 2). Environmental factors, which might represent physical, social, or jointly physical and social environments, are external to a given user and defined by the composition of the interaction situation. Examples include where the interaction is taking place (the privacy of space factor), who the co-users are (factors of the owner's presence, familiarity, and social hierarchy between co-users), and how the co-users are positioned (factors of proximity to the device and between co-users). Environmental factors can be explicitly manipulated and either directly sensed, or inferred, by the system to assess the interaction context. Unlike environmental factors, user-centered factors are internal to a given user and cannot be sensed or inferred by the system without the user's self-report. In our classification, these user factors include the sense of responsibility, autonomy, and self-efficacy; as they are experienced by each of the co-users in a multi-user scenario. We then validated the fitness of this classification for conversational systems in a user study exploring various scenarios of use.

Overall, our results led to design implications that highlight the importance of physical and social environments on future system design. To apply the overall results to the design space of natural language communication systems in multi-user scenarios, we further derived a corresponding model (Figure 1), which encompasses factors from the classification and additionally provides a conceptual separation between physical and social environments. The theoretical model offers a systematic understanding of the factors that are associated with multi-user interaction patterns, i.e., what factors affect who interacts with a system and when, in multi-user scenarios. The implications of this structured synthesis contribute, first, to the understanding of how to bridge our accumulated knowledge on graphical user interfaces with the needs of natural language communication systems design. In the future, this model can be used to measure the relative weight of each factor and their interdependencies. Additionally, the holistic and systematic view on these factors provides an approach that allows designers to be more deliberate when deciding and articulating how specific features of a natural language communication system support multi-user interactions, e.g., informs the system's awareness of environmental factors (sensing and inferring - physical and social environments) as well as its ability to account for factors internal for each co-user, which currently cannot be sensed.

The paper first presents the results of the literature analysis, structured according to the derived classification of factors affecting interaction patterns in multi-user scenarios. We then show the results of the experimental study (n=100), conducted as an initial validation of the classification fitness for natural language communication systems as example of voice interfaces. Finally, we conclude by synthesizing our theoretical and empirical findings into the model, and discussing the theoretical and design implications of the model.

2 BUILDING A THEORETICAL MODEL: LITERATURE ANALYSIS

The goal of this paper is to explore what situational factors affect interaction patterns in multi-user scenarios. In particular, we were interested in what factors affect input negotiation when several users interact with the same device, when the device presents a natural interface with no clear token of control, e.g. a voice interface. Due to the paucity of research in this area, we begin addressing this question, by, first, analyzing the relate literature broadly covering multi-user interactions, which includes multi-user interactions with diverse types of technology, beyond natural user interfaces. Based on this analysis, we synthesize a classification of factors affecting interaction patterns in multi-user scenarios (Figure 2). The classification distinguishes environmental factors (external to a given user and defined by the interaction environment) and user factors (internal to a given user in an interaction scenario). In this section, we first describe the review method, and then we present the results of our literature analysis, structured according to the suggested classification.

2.1 Method

The body of the covered literature was initially collected via Google scholar, with emphasis on recently-published works. The search was performed using a set of keywords that included but were not limited to: multi-user interactions/devices/interface, group interactions, sharing, co-use, and all combination between those and different types of technology, such as: tabletops, conversational agents, interactive walls, smart homes, Internet of Thing. The papers were reviewed and assessed according to their fitness to the research goal described above. The body of the analysed research included 124 papers from diverse HCI venues, including CHI/TOCHI, CSCW, Ubicomp/IMWUT, DIS, and GROUP. The factors affecting multi-user interaction patterns, covered in the papers, were synthesized by the research group using affinity diagrams. Specifically, in this paper, we present a model (Figure 1), structured around a classification of factors affecting interaction patterns in multi-user scenarios (Figure 2).

2.2 Environmental Factors

The first group of factors, identified as affecting multi-user interaction patterns, includes external factors, i.e. defined by the environment in which a particular multi-user scenario is taking place. In the model (Figure 1), developed based on the suggested classification (Figure 2) we differentiate between users' physical environment and social environment. While some factors are specific to the physical environment only: *Proximity to the Device and Other users* and *Owner's presence*; others are factors of the social environment only: *Familiarity Between Co-users* and *Social Hierarchy*; and finally *Privacy of Space* is shared between these two types of environments.

2.2.1 Privacy of Space (Physical and Social Environment). While physical space is constructed of all tangible objects around us, the social space is a conceptual term that refers to a multi-dimensional concept, in which we are all present as different agents with a particular position [13, 14]. Physical and social spaces are inevitably intertwined with each other and are interdependent [137]. For instance, Terrenghi et al. [124] discuss how the physical space can affect the social ecosystem around an interaction device. In this paper, we refer to the privacy of space as *an expected breadth of the potential audience*, differentiating public spaces (e.g. streets of a city), semi-, or "in-between" spaces (e.g. a school or a workplace), and private spaces (e.g. home).

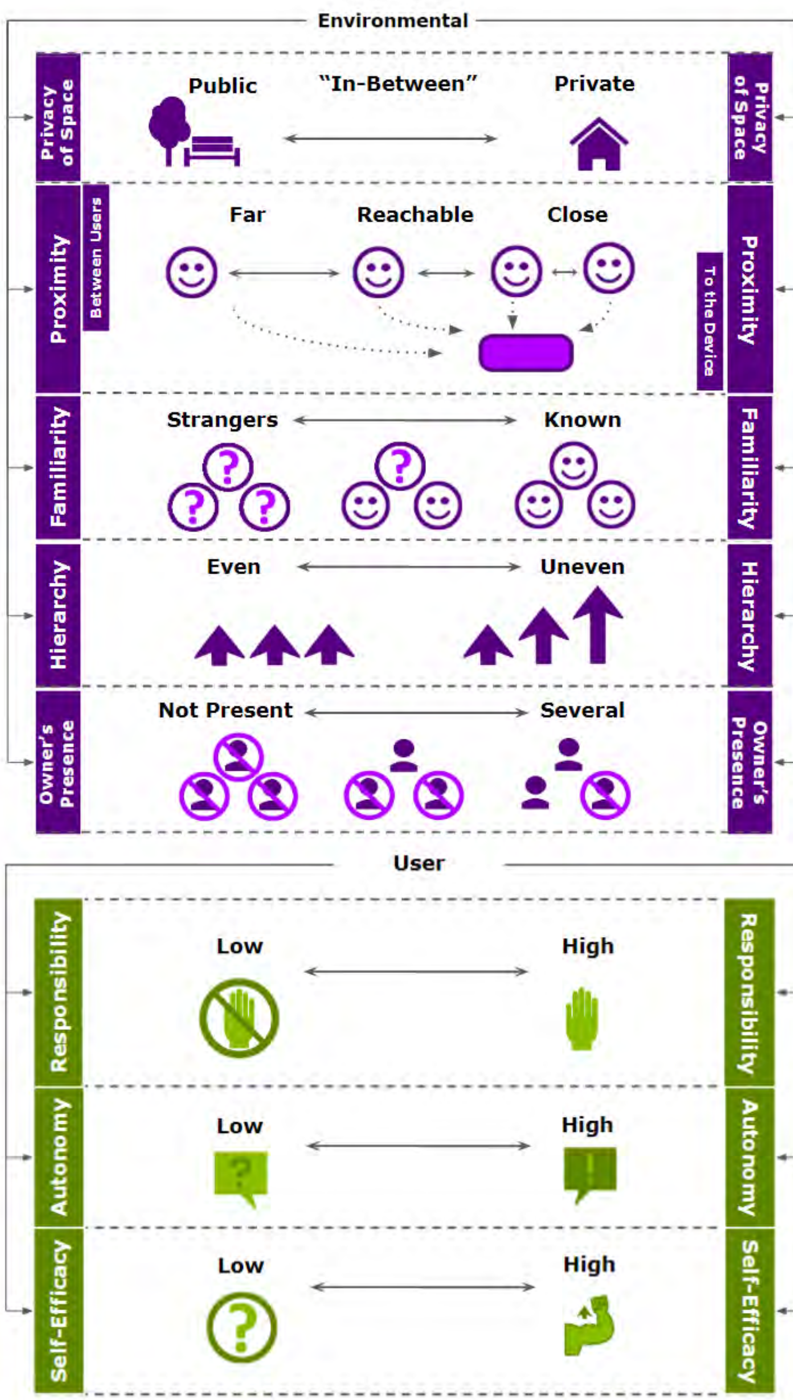

Fig. 2. Classification of factors affecting multi-user interaction patterns. The classification distinguishes environmental (external) and user-centered (internal) factors, and specifies the continuums, elicited to define each factor.

Multi-user interactions in *public spaces* are characterized by higher likelihood of encountering unfamiliar co-users [60] and having a broad audience [21, 31, 102, 111, 112]. The effects of potential audience facilitate the perception of the interaction space as a unique "performance space" [9, 140], changing social behaviors in response to the environment's feedback [45, 140]. For example, users might try to entertain the audience [21, 102], or experience the social pressure to interact "properly", without making mistakes [12, 16]. However, while interactions in public spaces indeed often allow to observe co-users' actions [31, 97, 102] and learn more about the system [16, 85, 137], unfamiliar simultaneous co-users tend to structure their work to stay independent from each other [77].

The degree of privacy of the interaction space grows alongside the likelihood of knowing potential co-users [15, 59]. Therefore, there is a need to approach "publicness" of the interaction space gradually, e.g. "publicly private" and "privately public" behaviours and self-presentation styles discussed by Lange [71] and Papacharissi [99] respectively. While some researchers consider the differences between semi-public and semi-private spaces (e.g. [31, 39, 56, 59]), the lack of consensus on their boundaries motivates other researchers to avoid any fixed definitions. For instance, Can and Heath [19, 20] suggest to term them jointly as "in-between" space. Examples of "in-between" spaces can include hospital environment [37], work environments [123, 128], classrooms [1, 54, 98], community centers [77], etc. Overall, the general assumption of users in "in-between" spaces is that they would probably work towards a shared goal, may it be a better studying environment, resolving a work conflict, or to increase productivity and support decision making [22, 42, 59].

Finally, multi-user interactions in *private spaces*, e.g. at home [61, 65, 94], tend to involve most familiar and trusted co-users [24, 43, 69]. Such interactions seem to be heavily influenced by the inequality of roles in managing the devices [26]. Specifically, while technologies in private spaces tend to be actively shared [18, 62, 80, 89, 122], they are usually associated with a particular user's account [62, 120] and have a primary user responsible for their configuration [44, 145, 146]. Correspondingly, the primary user ends up playing a dominant role [44, 145], even when a more nuanced agency and access levels for multiple users are more suitable and desirable [43, 62, 95].

Furthermore, primary ownership of the device by a particular user leads to this user's preferences and concerns about which types of data should be available to different co-user [64], strongly affecting patterns of shared use of technology [61, 122]. For example, exploring the practices of sharing of smart devices, Garg and Moreno [43] showed that the owners of shared devices establish specific rules regarding acceptable activities and content access. Breaking these rules in the use of shareable devices leads to reworking the rules or patterns of shared use; but breaking them in use of the owner's personal devices leads to revoking permission to use the device. In a similar vein, Brush and Inkpen [18] discuss the need to support both the shared usage model of appliances in domestic environments and the ability to access a personal profile.

2.2.2 Owner's Presence (Physical Environment). For the purpose of this research, we focus on the *owner's presence in the physical environment of a multi-user interaction scenario, whether in person or via social presence.* Such focus is motivated by our interest in exploring the multi-user interaction patterns, i.e. strategies to coordinate input from each co-user. For instance, developing a smart home multi-user application, Zeng and Roesner [146] found that some users are willing to allow visitors of their home to access and control the home devices, but only in presence of the home owner. Similarly, Karlson et al. [64] showed that owner's presence strongly influences the comfort level during phone sharing – the owner's discomfort would significantly rise if the phone were out of sight. Jacobs et al. [61] demonstrated that when a particular device is shared within intimate couples, users predominantly feel comfortable with their partners' accessing their devices and accounts only when they are both present. Finally, exploring access-control systems for the home environment, Mazurek et al. [82] found that users believed that being physically present during the file sharing process would allow them to exercise additional control over who accessed what, as well as providing social pressure to encourage desired behavior and prevent potential violations. Therefore, there is a differentiated line between the owner and the rest of the users since in most cases they cannot reach the full functionality of the device [24]; and in the cases of full access, the majority of co-users will not use those devices as the owner would, to show respect to the actual owner [61]. However, while all the discussed studies have focused on multi-user interactions from the owner's perspective, there is a drastic paucity of research on how the owner's presence affects input coordination from the perspective of each co-user.

2.2.3 Proximity (Physical Environment). In this paper, we consider proximity as the *factor reflecting the users' physical position and orientation with regard to each other* (proximity between users) and *the physical characteristics of a device* (proximity to the device) [5].

There is an extensive body of research that demonstrates the effects of user's proximity on interaction patterns. While some interface designs obligate user to get closer to the device to interact with it [77], interactions with other displays might require a certain distance, e.g. due to physical surrounding [77, 84, 124]. In public space, the specifics of input type might affect the discoverability and interaction visibility of the device [91]. For example, the grouping of people next to a device signals to others the presence of an interesting event in that location, drawing more users to this location and to the interaction with the device – otherwise known as the 'honey-pot' effect [16]. More distant interaction techniques, e.g. remote control, tend to be more discreet and don't draw as much attention [128].

Proximity has also been shown to facilitate the initiation of the interaction [5, 133], mediate the levels of users' engagement [16, 103], and correlate with the degree of user's collaboration [52, 54, 136]. For instance, in non-collaborative scenarios, users tend to keep some distance from each other within the device limitations [76], or might attempt to establish their control by excluding others from the device space [55, 76]. On the other hand, in collaborative scenarios, a shared goal seems to facilitates physical closeness between users to increase their efficiency [52].

The effects of proximity are tightly linked to the mechanisms of territoriality as a reflection of a perceived ownership towards an object [17, 100, 117, 125]. For instance, in co-use of visual displays, users tend to create an arc around the device, while a "manager" of the task stands in front of the display [112]. Close proximity, however, might cause the sense of invasion of each other's personal territory, leading to conflicts over interface real estate and even physical space [11, 31, 52, 76, 142]. At the same time, close proximity might facilitate users' coupling (i.e. dependency on each other in task performance) [31, 117, 123], prompting users to create rather flexible inner-territories [123], spatially organize a display to ensure approachability of artifacts for the co-user [43, 117], or even choose to interact in a less comfortable territorial setup to maintain their group's abilities [43]. Correspondingly, the proximity factor is linked to the user's ability to take control over part or the whole system [3, 52, 54], which is particularly noticeable in collaborations around sequential input interfaces, since the control over the devices needs to be handed over [54, 144]. A number of systems use different proxemic zones on interactive displays to trigger functionalities based on the user's location or to handle multi-user conflicts [3, 5, 118]. However, in addition to physical accessibility and ease-of-use [80], users' movements around displays are influenced by the corresponding social norms [16, 118] and act as signals to the rest of the group [40].

2.2.4 Familiarity Between Co-Users (Social Environment). For the purpose of this research, we understand familiarity as the *knowledge of the other person (varies in degrees of intimacy) and the behaviors around them, reflecting the socially acceptable behaviors corresponding to the degree of intimacy* [33, 108].

The current literature suggests that the levels of familiarity, first, affect the efficiency of multi-users interactions [33, 102]. For instance, when multiple strangers perform a shared task which requires tied coupling, e.g. performing a musical ensemble, the efficiency of such performance tends to be lower compared to the one with a familiar person [110]. The lack of familiarity damages the ability to synchronize their actions, which most of the time leads to a poor execution [114]. However, when users are familiar with each other, their performance efficiency can double compare to a team of unfamiliar user [114]. Familiarity with a co-user may reduce the "Curse of knowledge bias" [66], which suggests that when collaborating with someone else, one tends to assume that his personal information is known to all, and therefore judge the other performance based on their knowledge. When working with unfamiliar others, users may be more likely to show this bias [66].

Second, the level of familiarity between co-users seems to have an effect on the level of each user's control over the task and territory. For instance, users tend to use more explicit management of the situation when cooperating with strangers [34]. However, but when co-users are familiar with each other, they are more likely to assist one another and to behave more "freely" with each other's territory in a shared task [33]. Furthermore, sharing one's device with co-users requires prioritizing the simultaneous needs of multiple users [43], and familiarity between co-users affects the management of content access. In particular, when one allows others to use their devices, there may be some different "categories" for each of the potential co-users [93]. Those who are more intimate with the owner (usually family member or a life partners), may be granted higher-level access [64] compared to less familiar co-users (e.g., a friend or an acquaintance), whom the owner tends to supervise [81, 146].

2.2.5 Hierarchy (Social Environment). In a multi-user scenario, the factor of hierarchy refers to the *social acceptability for one person to outrank others in their right to control a device* [83]. The specifics of users' social hierarchy can be impacted by the user's social position (e.g., a house guest, a teacher, a parent, etc.) [29, 57, 77, 131, 146], their role in a collaborating team (a collection of responsibilities) [115, 129], or characteristics such as age [51, 94, 109] or gender [11, 25, 130, 143]. Through establishing social hierarchy in each particular situation, groups can ensure following social norms appropriate for different contexts [121].

The effects of the social hierarchy in multi-user interactions rely on each user's awareness of the social positions of others [96]. Some interaction contexts (e.g., between students and teachers [98], or parents and children [47, 146]) are characterized by more established specifics of social hierarchy. For instance, in family settings, parents tend to have higher positions in social hierarchy compared to children with respect to device interaction. Correspondingly, parents take a supervisory role in the co-use of technology by guiding and assisting children in managing the interactions [22], limiting children's access to the devices [57, 102, 131, 146], and controlling the consumed content [77, 131]. The parental supervisory role also includes their responsibility for how the child's interaction impacts other users, (e.g., interfering or distracting interactions [55, 102]).

In some interaction contexts, identifying appropriate social hierarchy might be more challenging [82, 122]. Overall, each person tends to have a combination of different social roles, e.g. inter-personal and within-team roles [135], continuously switching between them according to the relevance to a particular interaction [78, 129]. The formalized aspects of hierarchy, such as formal ownership of the device or a project, can result in one user's greater access to more of the system functions compared to other users [61, 129, 146], supporting the management capabilities of the higher-hierarchy users [121]. However, high-tension environments that are usually characterized by higher collaboration and require fast response have been demonstrated to suffer from a formalized interaction hierarchy [70]. Similarly, social hierarchy can be out-weighted by the importance of specific outcomes. For instance, families might allow younger children to interfere with others' interaction for the sake of learning [43], or lower-hierarchy users can "overwrite" a peer or a higher-hierarchy users to intentionally create an amusing situation [6, 27, 102]. While some interfaces attempt to map and categorize design guidelines of the system's behavior in different scenarios [7, 86], most of the current solutions do not draw user distinctions to reflect the complexity of the social hierarchy. For instance, the majority of the smart speakers empowered with conversational agents mark all users as equal, without addressing the different social hierarchies they might have. As a result, a child can override his parent's request - an action that couldn't have happened outside of this multi-user interaction [105, 116].

2.3 User-Centered Factors

The second group of factors, identified as affecting multi-user interaction patterns, includes factors internal to each actor in a multi-user scenario. In particular, in the suggested classification, this group includes factors of the user's (1) sense of responsibility for a particular technology, (2) sense of autonomy in using this technology, and (3) sense of self-efficacy.

2.3.1 User's Sense of Responsibility. The user's sense of responsibility towards a particular technology or a device reflects their *voluntary or enforced obligation to take care of it, including related performances, consequences, and issues* [47, 67].

A broad body of evidence from the literature suggests that the user's sense of responsibility affects multi-user interaction patterns. For instance, exploring collaborative writing processes, Larsen-Ledet and Korsgaard [72] found that while co-writers can share the overall sense of ownership over the document, they tend to feel responsibility specifically towards their own contribution. Wang et al. [134] found a strong desire from collaborating writers to be able to display each collaborator's responsibility and contributions over time. Indeed, Yuill and Rogers [144] argue that higher awareness of others' actions and intentions presents is one of the mechanisms for the success of multi-user collaborative interfaces. Similarly, work by DiMicco et al. [30] showed systematic effects of providing real-time awareness of speaker participation on group communication and collaboration; but, paradoxically, they found that in some cases, such awareness harmed other collaboration success measures (e.g., decreasing productivity and equitable participation). Additionally, the effects of displaying actions and responsibility of a given user has been explored in the context of multi-user interactions in home environments and digital housekeeping [27, 47, 94]. For example, Niemantsverdriet et al. [94] explore the design space for multi-user interaction with domestic systems by adopting the social translucence framework by Erickson and Kellogg [36] and investigating the corresponding constructs of visibility, awareness, and accountability.

Exploring groups collaboration over digital tables, Ryall et al. [113] showed that users separate the tabletop display into areas according to their reachability for one or for several users. Their study found that one's "personal" sections were clearly seen as the responsibility of this particular user, while "shared" sections of the table were the responsibility of "someone" (often not them) and required group coordination. Scott and Carpendale [118] suggested that types of tabletop territories (e.g. personal, group) provide common social protocols for collaboration by clarifying which areas of the shared display are available for individual or joint task work and for delegating task responsibilities. On the other hand, Tang et al. [123] found that when users have joint responsibility for the outcome of the task, they generally prefer to work together, regardless the task structure.

Thus, the user's sense of personal responsibility as well as their awareness of recognized responsibility of each co-user affects their interaction patterns with technology. Yet, there is a noticeable paucity of research exploring how the degree of intelligence of a system affects the role of personal responsibility in multi-user interactions. Specifically, system's intelligence allows users to delegate aspects of a task performance to it. Such delegation of responsibility to the system implies reduced control over the system's performance [58, 88], which could be expected to affect the interaction pattern, both for single-user and multi-user scenarios. For instance, research on smart home environments shows that users are often willing to delegate their responsibility to smart systems [119, 139]. However, it is still unclear whether and how this affects other family members in their interactions with these systems, especially given that users tend to feel higher levels of responsibility when the delegated task outcome is successful [132].

2.3.2 User's Sense of Autonomy. The sense of autonomy reflects the user's *internal judgement of their capability to independently initiate decisions and actions with a particular technology* [46, 47, 67].

In a multi-user scenario, one's sense of autonomy affects their level of collaborative contributions and is often influenced by social hierarchy, e.g. in child-parents relationship [57, 68, 131]. Consequently, the sense of autonomy can both affect and be affected by the level of control accessible to the user. Testing a prototype for a smart home multi-user application, Zeng and Roesner [146] found that users, concerned about other family members making changes to control policies or device configuration, would set the control possibilities of these members at the child privilege level, thus, restricting their autonomy. On the other hand, some users wanted to allow visitors (e.g. guests or domestic workers) restricted access and control over the home devices, thus, increasing the visitors' autonomy.

Additionally, one's sense of autonomy can be influenced by the specifics of control mechanisms. For example, based on a long-term study on a shared lighting system in an open plan office, Van de Werff et al. [128] found that control interface affects user's sense of autonomy. Specifically, the study showed that having a control interface on a personal multi-purpose device or on a central device dedicated to lighting, influences whether people make individual or more collective lighting adjustments and decisions.

Furthermore, we suggest to consider the user's sense of autonomy in interactions with a technology as two-fold: the autonomy in initiating the interaction and the autonomy in executing specific tasks using the system. The need for such distinction becomes specifically apparent in multi-user scenarios, particularly due to the privacy considerations (e.g., [69]). Exploring ethical concerns of using smart devices in the home environment, Seymour et al. [119] discuss how people associate using smart speakers with a risk of compromising the privacy of others in their environments, e.g. family members. Research on technology sharing practices in intimate couples [61] shows that although a user might sense autonomy in initiating interaction with a shared device (e.g. laptop), the autonomy in execution of tasks depends on the type of accessed context (i.e. public, tailored/personalized for one user, or private).

2.3.3 User's Sense of Self-efficacy. The sense of self-efficacy reflects the user's *judgement of their capability to successfully perform a task and competence to control the technology* [46, 67].

The level of the user's sense of self-efficacy has been demonstrated to affect their strategies to overcome difficulties or technical barriers [75, 87], interpretations of causes of unsuccessful interactions [87, 106], and overall willingness to use the technology [75, 127]. Specifically in multi-user scenarios, the existing literature mostly covers the effects of the user's self-efficacy on their level of initiative in interaction, and on potential social dynamics between co-users. For instance, while past experiences significantly influence the way users expect to interact with new technology [50, 77, 85], young children tend to be more willing to interact with new and unfamiliar systems [85, 111], usually through playful exploration [131]. Older users, on the other hand, tend to demonstrate higher resistance in adoption of new technology [32, 127], and often rely on others, e.g. relatives, to assist them [29]. Correspondingly, users that had a chance to interact with the system, especially if the interaction was successful, tend to find themselves in a tutoring or managing role, regardless of other social hierarchies [43, 85, 102, 106, 138]. For instance, exploring the adoption of smart homes with non-expert household members, Geeng and Roesner [44] found that there is often the leading "active" user who takes initiative to learn about and use devices, while "passive" users adapt to their decisions and rely on them to make changes, thus, practically, having access to less functionality and information than active users. Research also demonstrates that more technologically-savvy users tend to be more open and feel more comfortable towards interacting with new technology [77, 138], especially if it shares similarities with systems encountered earlier [50, 85, 106]. Thus, the user's sense of self-efficacy is affected by the recognizable/familiar aspects of interaction design and system's feedback matching users' mental model [73, 75].

3 EXPERIMENTAL VALIDATION

The second phase of this research presents an empirical user study, which focused on participants' interpretation of interaction patterns in multi-user scenarios. These empirical results allowed us to provide an initial validation of the proposed classification of factors and to gain insights into the applicability of this classification to multi-user interactions scenarios with natural user interfaces.

3.1 Study design

The design of the experimental validation followed a within-participant model and included a presentation of 12 stimuli with a questionnaire for each stimulus. Each stimulus included an image of an interaction scene and a verbal description of the scene. The set of questions for each stimulus was designed to capture the role of each of the factors, identified in section 2, in participants' external perception of the interaction situation. The choice to focus on an external bystander's perception is motivated by its similarity with the system's perspective. The following subsections describe the allocation of the factors into dependent and independent variables; the design of image stimuli representing various multi-user interaction scenarios; the design of the questionnaire enabling us to gather participants' perception of the different factors for each stimulus; the participants who took part in the study; and the study procedure.

3.1.1 Study Variables. In the literature analysis (section 2), we identified and classified eight factors as affecting multi-user interaction patterns. The goal of the study being to assess the role of each factor in the perception of a character as interacting with a device, the primary dependent variable was whether a character is perceived as an *Interactor*. The classification discriminates environmental and user factors (Figure 2) and forms the basis for the study variables with: environmental factors representing independent variables manipulated through the stimuli design, and user factors representing dependent variables due to their internal nature. The factor of the owner's presence was manipulated to represent a variable of ownership (i.e., a character being perceived as an owner) since the effects of the owner's presence cannot be assessed in a per character analysis. Following the same rationale, the factor of familiarity between co-users, which can only be captured in per scene analysis, was omitted from study variables.

Correspondingly, the **independent variables** included: *Privacy of space* (3 categories: private, in-between, and public), *Proximity* (2 categories: proximity user to device and proximity between co-users), and *Hierarchy* (3 categories: even and uneven (low and high). The **dependent variables** included: the perception of a character being an *Interactor* with the device, the perception of their *Ownership* of the device, their *Responsibility* towards the device, and their *Autonomy* and *Self-efficacy* with regards to operating the device. For the summary of the variables and the corresponding coding system see Table 2.

3.1.2 Stimuli Design. The set of stimuli included 12 images of multi-user interaction with a device and a corresponding verbal description of the presented scene. Each image included 3 characters (all unique potential users), and one device with a natural interface (without a physical token of control). Each character was labeled with an arbitrarily assigned name to allow participants to identify the said character in the description. All stimuli were presented at the same size (width: 400px, height: 315px) and were located in the center of the screen. Stimuli set was equally split into three groups of four, each group representing a different level of *Privacy of space* (private, in-between, or public). Within each group, stimuli were equally distributed to represent even and uneven (low or high) hierarchy; and different proximities between co-users, and between users and the device (see figure 3 as an example). The images for the set of stimuli were gathered via online image search and were selected based on the following criteria:

(1) Exactly three human characters are present in the image to establish a consistent number of potential co-users.
(2) Each character can be perceived as interacting with the device, e.g., the characters are looking at the device, or pointing at it.
(3) The position of each character and the device in relation to the characters can be seen clearly without occlusion on the image.
(4) Scenes are taking place in (1) private (e.g., home) spaces, (2) in-between (e.g., hospital), or (3) public space (e.g., street, mall).
(5) To control the effect of the presented device, the stimuli were equally distributed to demonstrate interactions with a smart speaker and a robot.

We did not consider images that involve visible feedback that could point out to a specific character (e.g., a robot with eyes, looking at a specific character) and devices with a clear token of control (e.g., a remote control being held by a character).

Fig. 3. Example of a stimulus image with the following description: *Three brothers (Tyson, Jeffery, and Seth) are together at home. On the floor, there is a smart speaker with a conversational agent (e.g., Alexa or Google Home).*

3.1.3 Questionnaire Design. Each stimuli was followed by a questionnaire designed to capture the participant's perception of each dependent variable in the prompting scene. The questionnaire included the following questions.

- Interactor: *In your opinion, who is/are interacting with the device in this scene? (mark all that apply)*
- Owner: *In your opinion, who is the owner of the device? (mark all that apply).*
- Responsibility: *In your opinion, how responsible are each of the characters for the overall maintenance of the device and its proper functioning?* 7-point Likert scale for each character.

- Autonomy: *In your opinion, how independent is each character from the other 2 people in the image in initiating action with the device?* 7-point Likert scale for each character.
- Self-efficacy: *In your opinion, how confident is each character in their ability to use this technology?* 7-point Likert scale for each character.

Additionally, participants were invited to provide open-ended explanations for each of their responses.

3.1.4 Participants. In total, 100 participants were recruited for the study on the Amazon Mechanical Turk (mTurk) online crowdsourcing platform. The Turkers were sampled with an excellent performance history, HIT approval rate ≥ 97, and an approved number of HITs ≥ 100, all located in the USA. Out of the 100 participants, 96 passed the attention question (see study procedure below). On average, participants were 41.5 years old (SD = 11.2 y.o.) ranging from 24 to 76 y.o.; 73.9% with a college degree or higher; 52% self-identified as female, 48% as male. The average study completion time was 47 minutes and participants were paid on average US$5.17, including an additional bonus ranging from US$0.5-$2 for participants who put extra effort into answering the questionnaire, such as elaborating on the open questions.

3.1.5 Study Procedure. Our research method focusing on perception using static images is based off prior work [53, 63, 79, 141]. Two pilot studies (n=5, n=10) were conducted to verify the protocol and to ensure the clarity of the image stimuli and questions. Consequently, several questions were rephrased, and two image stimuli were replaced. At the beginning of the experiment, participants were presented with a description of the study and asked to read and sign an electronic consent form. They then received instructions on how to fill out the questionnaire. In the next step, they were asked to fill in a demographics questionnaire. Participants were then presented with each of the 12 stimuli and questionnaires, one by one, assigned in a random order for each participant. Halfway through the questionnaire, participants were asked to answer an attention question, for which they were asked to identify the names of the characters on a prompting image.

4 DATA ANALYSIS AND DISCUSSION OF RESULTS

To analyze the participants' perception of each factor in different scenarios and the effects of each factor on the perception of a character as an interactor with the device, we first prepared the data.

The values of the dependent variables (*Interactor, Owner, Responsibility, Autonomy, and Self-Efficacy*) were extracted from the participants' responses to the questionnaire. The values of the independent variables (*Privacy of space, Proximity, and Hierarchy*) were based on the stimuli. The dependent and independent variables were then coded, data was normalized, and datasets were formed. The datasets included a full dataset (3,456 data points) and three sub-sets corresponding to the different types of *Privacy of space* (private, in-between, public) following the three major groups of stimuli (1,152 data points each).

The aim of the empirical study was to provide an initial validation of the classification of factors by exploring whether and how each factor contributes to the perception of interaction with a device, in diverse multi-user settings. Within our analysis, we considered two questions. The first one related to the effects of each factor on the perception of a character as an interactor with the device (per character), and the second one focused on how each factor was perceived for each stimulus (per scene), including across different types of spaces. The following subsections describe the data preparation, the analysis process, and the results for each of these questions.

Table 1. Correlation table between the explanatory variables of the model. A Cramer's V test was used to calculate the correlation of the categorical (*Privacy of Space, Proximity User-Device, Proximity Between co-user, Hierarchy* and the binary variable (*Owner*). A Pearson's correlation was used on the ordinal variables (*Responsibility, Autonomy,* and *Self-Efficacy*. Statistical significance is represented by ** ($p < 0.01$); * ($p < 0.05$).

		Cramer correlation					*Pearson correlation*		
		Privacy of Space	Proximity		Hierarchy	Owner	Responsibility	Autonomy	Self-Efficacy
			User-Device	Between co-users					
Privacy of Space		1							
Proximity	User-Device	0.423**	1						
	Between co-users	0.422**	0.396**	1					
Hierarchy		0.081**	0.28**	0.23**	1				
Owner		0.456**	0.189**	0.273**	0.244**	1			
Responsibility		0.34**	0.171**	0.209**	0.199**	0.65**	1		
Autonomy		0.092**	0.089**	0.161**	0.132**	0.138**	0.179**	1	
Self-Efficacy		0.234**	0.167**	0.116**	0.099**	0.38**	0.466**	0.301**	1

Table 2. Summary of variables and corresponding coding system.

Variable Name		Variable Type	Description	Coding Element (Value)
Interactor		Dependent	Interacting with the device	No (0) / Yes (1)
Privacy of Space		Independent	Type of Space	Private (0) / In-between (0.5) / Public (1)
Proximity	User-Device	Independent	Distance to the device	At arm's reach from the device (0) / 2-arm's reach from the device (0.5) / Further away from the device (1)
	Between co-users	Independent	Distance to other co-users	At arm's reach from all co-users (0) / 1 co-user is at arm's reach (0.25) / 2-arm's reach from all co-users (0.5) / 2-arm's reach from a co-user and further away from the other (0.75) / Further away from all co-users (1)
Hierarchy		Independent	Level of Hierarchy	Uneven (Low (0) / High (1)) / Even (0.5)
Owner		Dependent	Being an owner of the device	No (0) / Yes (1)
Responsibility		Dependent	Level of responsibility	Normalized 7-point Likert scale
Autonomy		Dependent	Level of autonomy	Normalized 7-point Likert scale
Self-Efficacy		Dependent	Level of self-efficacy	Normalized 7-point Likert scale

4.1 Per Character Analysis

The following subsections describe how the data was coded and analysed for the per character analysis.

4.1.1 Data Coding. The study dependent and independent variables resulted in raw data, which was presented using one of three scales: binary, ordinal, and categorical. To prepare for analysis, the data was transformed as follows: the binary data (*Interactor* and *Owner*) was kept unchanged; the ordinal data (*Responsibility, Autonomy*, and *Self-Efficacy*) was normalized from a 7-point Likert scale into a value in a 0-1 range; and the categorical data (*Proximity* and *Hierarchy*) was assigned a numerical value describing its category in a 0-1 range (Table 2).

4.1.2 Analysis Process. To understand the impact of the identified factors on the perception of interactor, we created a regression model, which was designed to verify the underlying assumption that the factors, composing the model of multi-user interactions, can predict the perception of an interactor. Correspondingly, we used a Generalized Linear Mixed Model regression (GLMM) which is used to predict a binary variable by transforming both fixed-effects and random effects into linear predictor [38]. In the model, participants were treated as a random factor. The variables of *Owner, Responsibility, Self-Efficacy, Autonomy, Proximity*, and *Hierarchy* were treated as explanatory to the explained (primary dependant) variable of being perceived as an *Interactor.*

Before running the GLMM, and to investigate the relationships between the explanatory variables, we first verified the correlations between them. The correlation for categorical and binary variables – *Privacy of space, Proximity, Hierarchy, Owner* – were calculated using a Cramer's V statistical test and the correlation for the ordinal variables – *Responsibility, Autonomy, Self-efficacy* – were calculated using a Pearson's test. Table 1 presents the resulting correlations, all showing significance ($p < 0.01$).

While most of the correlations were moderate, the *Privacy of space* had correlations > 0.4 with the variables (*Proximity* (User-Device & Between co-users) and *Owner*). We then measured potential multicollinearity between *Privacy of Space* and these variables using the Variance Inflation Factors (VIF). The test results showed a moderate multicollinearity for the *Privacy of space* variable (VIF = 3.99) [28]. However, given that this value rounds up to the threshold of 4 [49], we opted to run the regression model first with *Privacy of Space* as a single explanatory variable (see Table 3) and to separate it from the global GLMM (see Table 4). Note that all models accounts for participants' responses for each character individually, and did not take into account potential relationships between the characters.

4.1.3 Results. The output of the GLMM for all four datasets is presented in Tables 3 and 4. Each model includes the name of the explanatory variables, including the coding of the categorical ones, and the fixed effects of the odds values, in each dataset. The baseline group is represented by the intercept, composed of all the 0 values of the categorical explanatory variables, as well as other explanatory variables. To fully understand the effect of each explanatory variable on the explained one, each value should be interpreted as a multiplication factor which can then explain the direction of the prediction. We further describe the role of each factor on a character being perceived as *Interactor* for different *Privacy of space.*

Privacy of space. This factor has a significant effect and we found that characters are more likely to be perceived as interacting with the device in private and in-between spaces as compared to public spaces. For instance, if the scene depicts a home or school environment, a character is more likely to be seen as interacting with a device than on the street or in a mall.

Proximity. This factor is divided into two subfactors: the proximity between a character and the device (User-Device) and between characters (Between co-users) which both proved significant.

Table 3. GLMM output on the effects of the *Privacy of space* factor on explaining the *Interactor*. Statistical significance is represented by: * ($p < 0.05$).

	Values of the categorical data	Full dataset
Intercept		1.124
Privacy of Space	*In-between (0.5)*	1.185
	Public (1)	**0.773***
AIC	4584.2	
R^2 (R2c)	0.131	

Table 4. GLMM output on the effects of all factors on the perceived *Interactor* in multi-user scenarios. Factors with empty cells (-) were not kept in the regression model. Statistical significance is represented by: ** ($p < 0.01$); * ($p < 0.05$).

		Values of categorical variables	Full dataset	Private	In-between	Public
Intercept			**2.188****	**4.707****	**0.123****	0.499
Proximity	User-Device	*2-arm's reach (0.5)*	**0.483****	**0.078****	1.368	1.642
		Further away (1)	**0.295****	**0.022****	**0.028****	0.985
	Between co-users	*1 co-user is at arm's reach (0.25)*	**0.282****	1.534	**0.133****	-
		2-arm's reach from all (0.5)	**0.397****	**0.201****	1.344	-
		2-arm's reach from a co-user and further away from the other (0.75)	**0.040****	0.230	-	-
		Further away from all co-users (1)	**0.376****	-	0.933	**0.200****
Hierarchy		*Even (0.5)*	**0.348****	**0.085****	**7.493****	0.967
		Uneven - High (1)	**0.419****	**0.055****	**1.960***	**0.642***
Owner			**2.547****	**2.423****	**205.203****	**4.415***
Responsibility			**0.433****	0.954	0.687	1.311
Autonomy			1.293	0.825	0.958	1.495
Self-Efficacy			**6.508****	**9.689****	**25.508****	**4.208****
AIC			3815.2	1126.2	817.6	1391.9
R^2 (R2c)			0.426	0.449	0.811	0.404

The results demonstrate that, overall, the closer a character is to the device, the more likely they will be perceived as interactor. This effect is also significant in Private spaces. In in-between spaces, this effect is only significant when participants are further than 2-arm's reach away from the device. While the tendency to get closer to a device to interact is expected with devices that include a physical token of control (see subsection 2.2.3), we observe that this is also the case with natural interface devices when technically, input does not require close proximity. Furthermore, we did not observe statistical significance in User-Device distance in public spaces, which might be explained by the fact that when people interact with public displays for example, different types of interactions will occur at different interaction distances [133], therefore not necessarily requiring the user to approach the device to interact.

The factor of between co-users proximity also showed significant differences. We find that overall a character is most likely to be perceived as interactor when within arm's reach from the other two characters. They will be significantly less likely perceived as interactor when within two arm's reach or further away from the other two characters; and even less likely with only one character at arm's reach or when one is at arm's reach and the other further away. In private environment, significance difference is found when characters are at 2-arm's reach of either one or both co-users;

while in in-between spaces, significant difference is found when the character is at one's arm reach of only one other character. The model drops this factor for public spaces. These results highlight the importance of the distance between co-users in defining who will be chosen as interacting with the device, and how this distance could create some ranking behaviors, probably based off social norms between characters. In addition, it confirms that, as for user-device distances, proximity does not appear to play a role when interacting in public spaces. These results also lead us to believe that the position of the device, compared to each character individually and as a group has an affect on who is perceived as interactor. Further research is needed to understand how the factor of Proximity is interwoven between people and device.

Hierarchy. The data suggests that the factor of hierarchy has a highly significant effect across all datasets. Interestingly, the nature of this effect varies between different privacy of space. Specifically, in private spaces (e.g., at home) and in public spaces (e.g., on the street), higher social hierarchy significantly lowers the chances of a character to be perceived as an interactor, such that a parent is less likely to be seen as an interactor than a child. In in-between spaces, the nature of this effect is reversed – a higher hierarchy (e.g., an employer) significantly increases a character's chance to be seen as an interactor compared to those with a lower hierarchy status (e.g., employee). In the study materials, we defined *Hierarchy* both through the age of characters (children vs. adults) and professional relationship (manager vs. employee), but the latter has predominantly appear in in-between environments. This might potentially explain the negative correlation between hierarchy and interactions, since, while parents tend to have higher positions in social hierarchy compared to children and control their interactions [22, 57, 102, 131, 146], children are often allowed to interfere interaction of others for the sake of learning [43], and are generally more willing to interact with new systems [85, 111, 131]. In addition, we found that when a character is at an even level (i.e., no hierarchy) with the other two characters, they are significantly less likely to be seen as interactors in private and public spaces, but significantly more likely to interact in in-between spaces. This is indicative of the role of the social structures and norms and their part in choosing the interactor.

Owner. When observing the full dataset, the results show that being perceived as an owner significantly improves the chances of being perceived as interactor. This effect is significant in each dataset. It is even more prominent in in-between spaces, which means that if a character is perceived as the owner of the device in a semi-public or semi-private space (e.g., at work), then the person is more likely to be perceived as interactor.

Responsibility. The output on the full dataset shows that the factor of responsibility towards the device has negative effect on a character's likelihood to be perceived as an interactor, i.e., the lower perceived responsibility increases the character's chances to be seen as an interactor. However, for each particular type of privacy of space, this effect does not appear to be significant.

Autonomy. This factor did not appear to be a predictor of a character's likelihood of being perceived as an interactor.

Self-efficacy. The results show that the higher the perceived self-efficacy of a character, the more chances this character has to be chosen as an interactor. This factor has a significant effect across all datasets, i.e., the result holds across all types of privacy of space. This would suggest that the more confident a character seems to be in their ability to use the technology (i.e., perceived higher *Self-efficacy*), the more likely they are to be perceived as interacting with it.

To further understand our results beyond each individual character, we analyze our data for each scene.

4.2 Per Scene Analysis

The following subsections describe how the data was coded and analysed for the per scene (i.e., stimulus) analysis.

4.2.1 Data Processing. The data used in this analysis corresponds to the dependent variables extracted from the study questionnaire. For each stimulus, the following values were computed: Number of perceived *Interactors*, summing up the number of characters chosen as interacting with the device (none, single, multiple); Number of *Owners*, summing up the number of characters chosen as owner of the device (none, single, multiple); Level of *Responsibility* corresponding to the mean value of the responsibility scale; Mean level of *Autonomy*, computed as the mean value of the autonomy scale; and the mean level of *Self-efficacy*, computed as the mean value of the self-efficacy scale.

These descriptive values were calculated for all datasets and were then compared between the three subsets, i.e., different levels of *Privacy of Space*. For the binary variables (*Interactor* and *Owner*), we ran a within-group analysis using χ^2 (Figure 5), and a between-group analysis using a proportion test. For the other variables (*Responsibility, Autonomy*, and *Self-efficacy*), we used an ANOVA test with Tukey HSD post-hoc tests to identify differences between the groups, with the statistical significances reported in Figure 4.

4.2.2 Results. The results of the descriptive statistics are summarized for each of the four datasets in Table 5 and the significance of the differences is demonstrated on Figure 4. We further describe below how each factor was appraised by the participants.

Table 5. Overview of the distribution of responses of the participants for each dependent variable.

Factor		Full dataset	Private	In-between	Public
Interactor	None	15.5%	12.7%	8.5%	25.2%
	Single	45.7%	48%	49.5%	39.8%
	Multiple	38.8%	39.3%	42%	35%
Owner	None	57%	21.3%	54.5%	95.5%
	Single	23.5%	30.7%	35.5%	4.5%
	Multiple	19.5%	48%	10%	0%
Responsibility	Mean	2.5	3.7	2.6	1.4
	SD	2.2	2.4	2.2	1.2
Autonomy	Mean	4.3	4.3	4.1	4.5
	SD	2	2	2.1	2
Self-efficacy	Mean	4.5	5.2	4.5	3.7
	SD	1.9	1.6	2	1.9

Interactor. The most frequent response across all datasets was that the device is being used by a single character, whereas the least frequent response was that no one uses it. This data collaterally supports the initial assumption of interaction patterns, i.e., that in multi-user scenarios, users tend to engage with a device through non-simultaneous interaction actions. While the prevalence of a single character being seen as an interactor is consistent across the different levels of the *Privacy of space,* it should be noted in all types of space, the differences between perceptions of a single and of multiple characters as interactors are insignificant. Furthermore, the perception that nobody is interacting with the device is significantly more common for public spaces, and the perception of a single interactor is significantly less common compared to other environments. The joint

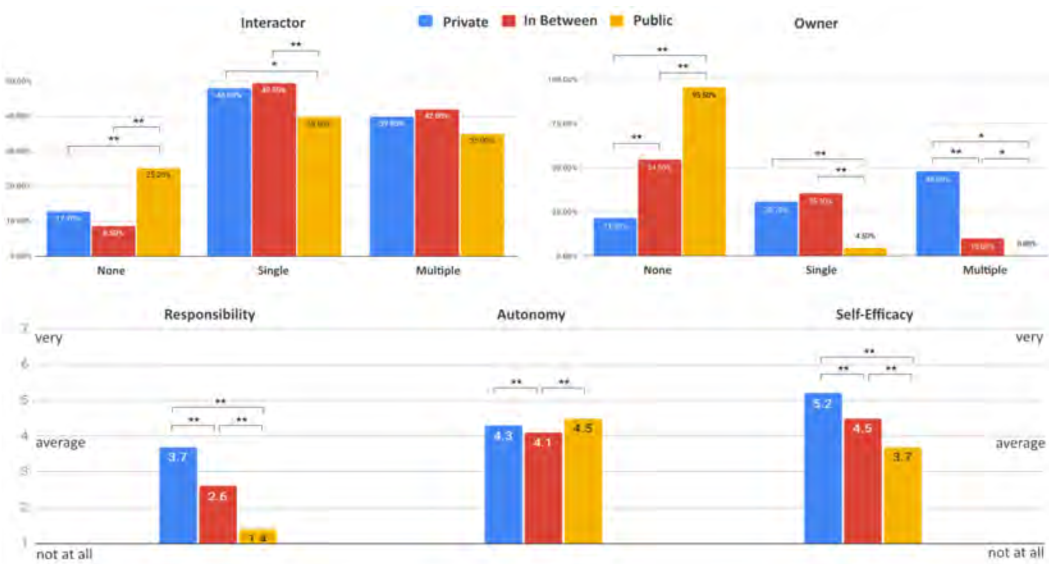

Fig. 4. Plotting of the responses distribution for each dependent variable, with a statistical comparison between different *Privacy of space* (Private, In-between, Public) for each variable. Statistical significance is represented by: ** ($p < 0.01$); * ($p < 0.05$).

consideration of this data with the results on the effects of the *Privacy of Space* factor (see section 4.1.3) further confirms that in public spaces, characters are less likely to be perceived as interactors in general. While the causes and mechanisms leading to this effect need to be further investigated, we note that, arguably, it is not yet common for people to be interacting with non-personal devices in public spaces, which may have influenced participants' interpretations.

Owner. In private spaces, ownership tends to be assigned to multiple characters (48%); while in public spaces, in almost all instances (95.5%), no character is perceived as an owner. Interestingly, our data shows high frequencies both for a single (35.5%) and no owner (54.5%) in in-between spaces. This evidence first illustrates the transitional position of interaction processes in in-between spaces, from public to private. Second, this finding opens a question on the perception on the nuances of ownership assignment in semi-public and semi-private environments, e.g., at work or in school. Given that the results of the per character analysis showed that if a character is perceived as an owner of a device, their likelihood of being seen as an interactor significantly increases (see the results for the *Owner* factor in section 4.1.3), the lack of ownership assignment in public spaces further contributes to the frequency of no character being seen as an interactor in these spaces. However, while private spaces most often include multiple perceived owners, the prevalent perception of interactors is still as a single character. This suggests that, although the perceived ownership affects the perceived role in interaction, this effect might not be linear and requires further investigation.

Responsibility. The perceived level of *Responsibility* is below average in all spaces. The lowest appears to be in public spaces (1.4 out of 7) and the highest in private spaces, still remaining below average (3.7). Furthermore, the perceived level of responsibility for in-between spaces is 2.6, confirming the transitional position of in-between spaces. These findings open a discussion on both the role and mechanisms of the users' sense of responsibility towards devices in multi-user

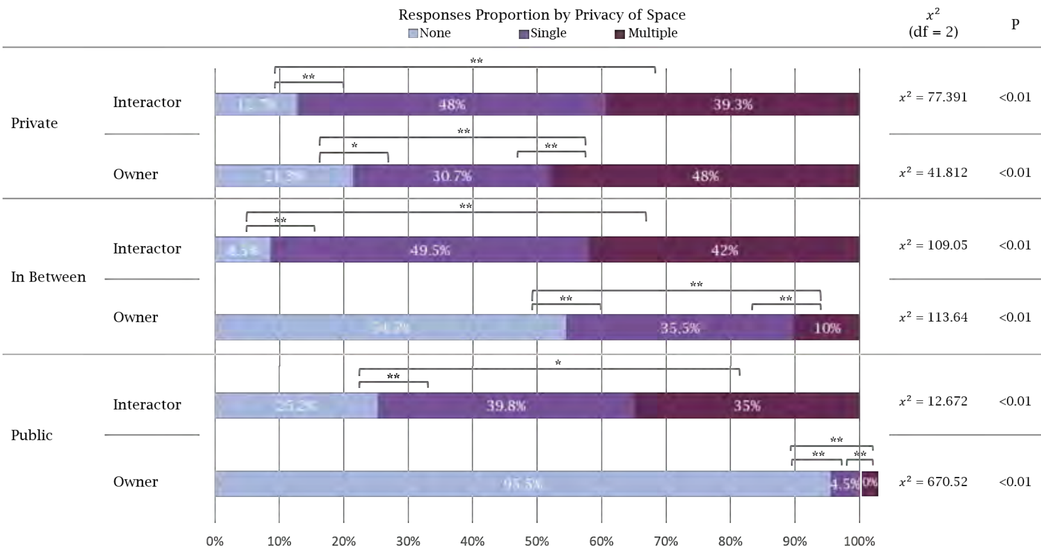

Fig. 5. Plotting of the responses proportion for the *Interactor* and *Owner* dependent variables, with a statistical comparison within each level of *Privacy of space* (Private, In-between, Public) for each variable. Statistical significance is represented by: ** ($p < 0.01$); * ($p < 0.05$).

scenarios, as well as the differences in the sense of responsibility in different levels of privacy of space (e.g., at home vs. at work vs. on a street).

Autonomy. Although, the perceived *Autonomy* level of the characters is around average in all spaces (4.3 out of 7), it is significantly lower in in-between spaces compared to other environments. Since the sense of autonomy towards a device reflects the perceived independence in initiating actions with this device, the lower levels of autonomy in in-between spaces (e.g., at work) suggest a need for a particular attention to interaction empowerment when designing for these environments. Furthermore, the difference between the participants' responses in the private space when compared to the public space was not statistically significant and they were perceived similarly. This could be due to the perceived equity of social landscape, i.e., social actors having similar "rights" to initiate actions, both in private spaces where multiple characters act as owners, and in public spaces where no character is an owner.

Self-efficacy. The sense of self-efficacy of characters, i.e., the perceived level of their confidence in interacting with a device, was observed to be the highest (and above average) in private spaces (5.2 out of 7). The lowest levels of self-efficacy appeared for public spaces, although it should be noted that the mean value is only slightly below the average (3.7). We found significant differences in self-efficacy between all types of Privacy of space. Arguably, these results could be corroborated by the fact that people are expected to be more experienced with devices in familiar spaces (e.g., at home) compared to devices situated in other shared environments; however, an in-depth understanding of these tendencies require further exploration.

5 DISCUSSION OF THE MODEL AND IMPLICATIONS

The goal of this work is to propose an initial model of multi-user interaction with natural interfaces by classifying the factors affecting co-use patterns in multi-user scenarios. The initial set of eight factors was derived from an extensive literature analysis and categorized into environmental and user factors based on the nature of these factors (i.e., external vs. internal). This structure aids in system design by offering a systematic approach that allows a developer to identify what specific features of a system should support multi-user interactions and how. The fitness of these factors for multi-user interactions with specifically voice interfaces as examples of natural interfaces, was explored empirically through an experimental user study. The results of the study provide an initial validation of the structure of the model and reveal the nuances of the significance and the effects of the constituting factors. In this section, we first discuss the heterogeneity of factors in the model, followed by the outline of the design implications on future interfaces supporting multi-user interactions.

5.1 Discussion of the Model

When empirically evaluating the fitness of the model for voice interface systems as an example of natural interfaces, we observe that while each factor has a role, these factors are not homogeneously affecting the perception of interaction. Scenarios when several users might need to interact with a system simultaneously might occur in different environments. In the current research, based on evidence from literature, we first defined the differences in these environments on a continuum from private, through in-between (i.e., semi-public), to public environments; referring to this factor as privacy of space. While other environmental factors reflect the further nuances in the composition of the interaction environment, the **privacy of space seems to offer a rather cumulative approach for separation of interaction contexts**, suitable for design purposes. In particular, HCI researchers often tends to position their work within application domains, e.g., smart home design (private space) [44, 119, 139, 146], design for work [118, 123, 128] or learning [1, 78, 98] (in-between space), or design for city environments (public space) [100, 102, 140]. Furthermore, our empirical results support such approach to the high-level separation of the environments by suggesting the differences in the role of other constituting factors on being perceived as an interactor in private, in-between, and public spaces. For example, scenarios in public spaces are characterized by significantly more often lacking an assigned owner of the system, lower levels of the average responsibility and self-efficacy. On the other hand, in private space, e.g., at home, the ownership is most often assigned to multiple characters, compared to other environments, and the average responsibility and self-efficacy assigned to the characters, are significantly the highest.

In addition, the literature analysis found proximity between co-users to be a reflection of shared ownership of a device or its content [117], as well as a sign of collaborative behavior between co-users [52, 112]. This was similarly observed in our empirical study where 48% of the participants perceived the device as owned by multiple characters in the private space (shared ownership) and as we found the proximity between co-users – as well as the proximity to the device – to be a significant predictor of interaction with the device. Overall, the study results, first suggest that, **although the distinguishing characteristic of voice interfaces is the lack of physical token of control over the system, territoriality and physicality parameters still hold relevant to these systems**. In a similar vein, exploring the effects of physicality of the device on the mental model of conversational agents, Lee et al. [74] found that users' perceptions, expectations, and interactions toward the agent differed depending on the presence of a physical entity. Second, these results suggest that, **in multi-user scenarios, the mechanisms of the perceived interactions with voice interface systems generally agree with the mechanisms defining multi-user interaction patterns with graphical interfaces**. Finally, the significance of the responsibility factor across all environments, but the lack of it for each particular environment might be potentially explained through the users' underdeveloped mental model of shared ownership of systems in general [43, 83, 128], and the natural interface systems specifically [8, 24, 74].

5.2 Leveraging the Model in Design

By systematically approaching the factors affecting input patterns of co-users, **the model offers an opportunity to navigate the multi-user design space and formulate design decisions based on the combination of relevant factors**. For instance, the model describes the social hierarchy between co-users (e.g., children and parents, workers and managers) as one of the environmental factors affecting who interacts with a system. In particular, our model details how people are more likely to be seen as interacting with a device in in-between (i.e., semi-public) spaces when there is no hierarchy between users, or when they have higher hierarchy over other co-users. Moreover, our empirical results suggest that the presence of the owner – also environmental factor – is exceptionally relevant in these in-between spaces. Both factors therefore become of a particular interest to the deployment of natural interface systems in spaces such as work environments, hospitals, or community centers. Furthermore, a conceptual separation of environmental and user factors addresses the diversity of the nature and sources of the identified factors, and informs the procedural heterogeneity of how a system can approach the assessment of these contextual parameters.

5.3 Leveraging Environmental Factors

The model includes five environmental factors, which we defined as being external to a given user and determined by the composition of the interaction situation, including where the interaction is taking place, who the co-users are, and how the co-users are positioned spatially both with regards to each other and to the device. While the environmental factors might represent parameters of physical, social, or jointly physical and social environments; **their external nature makes them potentially available for the direct assessment by the system through either sensing (physical environment) or inference (social environment)**. Indeed, this approach finds reflection in the design of context-aware systems. In particular, to capture the heterogeneous nature of context, researchers distinguish types of contextual data through the dichotomy of "physical" versus "logical" context [4, 7, 48, 107, 126]. Physical context refers to sensable environmental state (e.g., location, light, movement) [4, 48, 107], while the logical context describes users' state, experience, and activity [4, 48], which tends to be inferred based on a combination of parameters (e.g., "communication availability" of a user) [41, 90, 92]. Regardless of whether the environmental factors are directly sensed or inferred, the system's ability to systematically assess the composition and the interaction situation allows for designing autonomous context-aware adaptations for dynamically changing settings, as required for efficient support of multi-user interactions [101].

5.4 Leveraging User Factors

Unlike environmental (external) factors, **user (internal) factors affecting multi-user interaction patterns are currently accessible to a system only through the users' self-report**. Yet, the initial understanding of the structure of this internal context is critical for informing the design of multi-user interactions for targeted tasks and populations. For instance, the identified factor of self-efficacy, which was empirically shown to be relevant in all private, in-between, and public environments, is known to manifest differently in different age groups. Specifically, while young children tend to be more willing to interact with new and unfamiliar systems [85, 111], older users have a tendency for higher resistance in adoption of new technology [29, 32, 127]. **Interestingly, all three user factors – sense of responsibility, autonomy, and self-efficacy – represent a subset of dimensions defined for the sense of ownership of technology [67]**. While the question of ownership perception towards technological possessions currently remains in early stages for the HCI research community, particularly for shared ownership [47, 125], our results collaterally support the heterogeneity of the ownership dimensions, and suggest the different affects of these dimensions on multi-user interaction patterns in different environments.

6 LIMITATIONS AND FUTURE WORK

The initial experimental validation to assess the fitness of the model of multi-user interaction and its relevance for systems with voice interfaces was performed in an online experiment. It was designed to validate the role of identified factors in a bystander's perception of who interacts with a natural interface systems and why, in intentionally ambiguous scenes depicted in a set of prompting image stimuli. The advantages of the online format of the study include, first, the ability to access a socially diverse set of participants, minimizing the similarity bias occurring when recruiting from familiar social circles. Second, this format offers convenient presentation of prompting stimuli and efficient collection of a diverse body of quantitative data in controlled conditions.

However, some limitations of the method should also be acknowledged. For instance, the format of the data collection does not allow dynamic understanding of the scene or follow-up with participants to further expand the understanding of their responses. Thus, the data collection method provides high replicability but potentially lacks the contextual richness of the narrative, produced by purely qualitative methods. In our analysis, we acknowledge these shortcomings but argue that the format is suitable for the initial validation, focused on a quantitative approach. Furthermore, the study was designed to capture participants' perceptions of the scenes as a bystander. While the interpretations provided by the participants were formed based on their prior knowledge and experience, this approach to data collection can potentially affect the generalization of the results on actual behavioral outcomes and limit the predictive power of the model.

Consequently, we suggest that further research is required for detailed validation of the model. First, more investigations are needed to define the calibration, relative intensity, and inter-dependencies between identified factors. Second, further behavioral experimental studies would allow to ensure the persistence and relevance of identified factors in different interaction spaces. Finally, targeted studies with specific user groups, such as children, older users, co-workers; will provide insights into the potential variations of the relative intensities of the factors for diverse use-cases.

7 CONCLUSION

The goal of this work was to develop a systematic approach to the parameters affecting multi-user interaction patterns with a particular focus on natural user interfaces, and to create a theoretical framework of the factors that impact the way people use multi-user devices together. This paper presents the first systematic view on the factors affecting interaction patterns in multi-user scenarios with voice interfaces, as an example of natural user interfaces. The factors are organized into a model, which was first derived from the existing literature, and then preliminary validated through an empirical user study. The model distinguishes five environmental factors (external to a given user and directly available for the system through sensing and inference) and three user-centered factors (internal to a given user and unavailable directly for the system). By synthesizing theoretical and empirical findings, we explore the relevance of the factors in the model for conversational systems and discuss the model's implications for the development of future multi-user conversational interfaces.

8 ACKNOWLEDGMENTS

We would like to thank Dr. Jeremy Frey, Prof. Yisrael Parmet, and Woody Gover for their feedback and help with the statistical work. Many thanks to all members of the Magic Lab and in particular to Amir Lorch, Viviane Herdel, and Ori Fartook for their support.

REFERENCES

[1] Iyad AlAgha, Andrew Hatch, Linxiao Ma, and Liz Burd. 2010. Towards a Teacher-Centric Approach for Multi-Touch Surfaces in Classrooms. In *ACM International Conference on Interactive Tabletops and Surfaces (ITS '10)*. ACM, New York, NY, USA, 187–196. https://doi.org/10.1145/1936652.1936688

[2] Leonardo Angelini, Maurizio Caon, Jacky Casas, Federica Cena, Amon Rapp, Omar Abou Khaled, and Elena Mugellini. 2018. Ubiquitous Chatbots: Workshop on Wearable and Embodied Conversational Agents. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers (UbiComp '18)*. ACM, New York, NY, USA, 1652–1655. https://doi.org/10.1145/3267305.3274146

[3] Michelle Annett, Tovi Grossman, Daniel Wigdor, and George Fitzmaurice. 2011. Medusa: A Proximity-Aware Multi-Touch Tabletop. In *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology (UIST '11)*. ACM, New York, NY, USA, 337–346. https://doi.org/10.1145/2047196.2047240

[4] Matthias Baldauf, Schahram Dustdar, and Florian Rosenberg. 2007. A survey on context-aware systems. *International Journal of Ad Hoc and Ubiquitous Computing* 2, 4 (2007), 263–277. https://doi.org/10.1504/IJAHUC.2007.014070

[5] Till Ballendat, Nicolai Marquardt, and Saul Greenberg. 2010. Proxemic Interaction: Designing for a Proximity and Orientation-Aware Environment. In *ACM International Conference on Interactive Tabletops and Surfaces (ITS '10)*. ACM, New York, NY, USA, 121–130. https://doi.org/10.1145/1936652.1936676

[6] Diana Beirl, Nicola Yuill, and Yvonne Rogers. 2019. Using Voice Assistant Skills in Family Life. In *13th International Conference on Computer Supported Collaborative Learning - A Wide Lens: Combining Embodied, Enactive, Extended, and Embedded Learning in Collaborative Settings (CSCL 2019)*. International Society of the Learning Sciences (ISLS), Lyon, France, 96–103. https://repository.isls.org//handle/1/4586

[7] Victoria Bellotti and Keith Edwards. 2001. Intelligibility and accountability: human considerations in context-aware systems. *Human–Computer Interaction* 16, 2-4 (2001), 193–212. https://doi.org/10.1207/S15327051HCI16234_05

[8] Adam Ben-Hanania, Joshua Goldberg, and Jessica R. Cauchard. 2018. Multi-User Control for Domestic Robots with Natural Interfaces. In *Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia (MUM 2018)*. ACM, New York, NY, USA, 433–439. https://doi.org/10.1145/3282894.3289736

[9] Steve Benford and Gabriella Giannachi. 2012. Interaction as Performance. *Interactions* 19, 3 (May 2012), 38–43. https://doi.org/10.1145/2168931.2168941

[10] Frank Bentley, Chris Luvogt, Max Silverman, Rushani Wirasinghe, Brooke White, and Danielle Lottridge. 2018. Understanding the Long-Term Use of Smart Speaker Assistants. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 3, Article 91 (Sept. 2018), 24 pages. https://doi.org/10.1145/3264901

[11] Mehmet Ilker Berkman and Adem Karahoca. 2012. A direct touch table-top display as a multi-user information kiosk: Comparing the usability of a single display groupware either by a single user or people cooperating as a group. *Interacting with Computers* 24, 5 (2012), 423–437. https://doi.org/10.1016/j.intcom.2012.07.002

[12] Gilbert Beyer, Vincent Binder, Nina Jäger, and Andreas Butz. 2014. The Puppeteer Display: Attracting and Actively Shaping the Audience with an Interactive Public Banner Display. In *Proceedings of the 2014 Conference on Designing Interactive Systems (DIS '14)*. ACM, New York, NY, USA, 935–944. https://doi.org/10.1145/2598510.2598575

[13] Pierre Bourdieu. 1985. The social space and the genesis of groups. *Information (International Social Science Council)* 14, 6 (1985), 723–744. http://www.jstor.org/stable/657373

[14] Pierre Bourdieu. 1989. Social Space and Symbolic Power. *Sociological Theory* 7, 1 (1989), 14–25. http://www.jstor.org/stable/202060

[15] Harry Brignull, Shahram Izadi, Geraldine Fitzpatrick, Yvonne Rogers, and Tom Rodden. 2004. The Introduction of a Shared Interactive Surface into a Communal Space. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work (CSCW '04)*. ACM, New York, NY, USA, 49–58. https://doi.org/10.1145/1031607.1031616

[16] Harry Brignull and Yvonne Rogers. 2003. Enticing people to interact with large public displays in public spaces. In *Proceedings of Interact 2003 - Ninth IFIP TC13 International Conference on Human-Computer Interaction*, Matthias Rauterberg, Marino Menozzi, and Janet Wesson (Eds.). IOS Press, Zürich, Switzerland, 17–24. https://rauterberg.employee.id.tue.nl/conferences/INTERACT2003/INTERACT2003-p17.pdf

[17] Graham Brown, Thomas B. Lawrence, and Sandra L. Robinson. 2005. Territoriality in organizations. *Academy of Management Review* 30, 3 (2005), 577–594. https://doi.org/10.5465/amr.2005.17293710

[18] A. J. Bernheim Brush and Kori M. Inkpen. 2007. Yours, Mine and Ours? Sharing and Use of Technology in Domestic Environments. In *Proceedings of the 9th International Conference on Ubiquitous Computing (UbiComp '07)*. Springer-Verlag, Berlin, Germany, 109–126. https://doi.org/10.1007/978-3-540-74853-3_7

[19] Işın Can. 2012. *In-between space and social interaction: a case study of three neighbourhoods in Izmir.* Ph.D. Dissertation. University of Nottingham. http://eprints.nottingham.ac.uk/12637/

[20] Işın Can and Tim Heath. 2015. In-between spaces and social interaction: a morphological analysis of Izmir using space syntax. *Journal of Housing and the Built Environment* 31 (2015), 31–49. Issue 1. https://doi.org/10.1007/s10901-015-9442-9

[21] Heloisa Candello, Claudio Pinhanez, Mauro Pichiliani, Paulo Cavalin, Flavio Figueiredo, Marisa Vasconcelos, and Haylla Do Carmo. 2019. *The Effect of Audiences on the User Experience with Conversational Interfaces in Physical Spaces.* ACM, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300320

[22] Xiang Cao, Siân E. Lindley, John Helmes, and Abigail Sellen. 2010. Telling the Whole Story: Anticipation, Inspiration and Reputation in a Field Deployment of TellTable. In *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work (CSCW '10)*. ACM, New York, NY, USA, 251–260. https://doi.org/10.1145/1718918.1718967

[23] Jessica R. Cauchard, Jane L. E, Kevin Y. Zhai, and James A. Landay. 2015. Drone & Me: An Exploration into Natural Human-Drone Interaction. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, New York, NY, USA, 361–365. https://doi.org/10.1145/2750858.2805823

[24] Marta Cecchinato and Daniel Harrison. 2017. Degrees of Agency in Owners and Users of Home IoT Devices. CHI'17 Workshop: Making Home: Asserting Agency in the Age of IoT. https://discovery.ucl.ac.uk/id/eprint/1542529

[25] Prithviraj Chattopadhyay, Elizabeth George, and Arthur D. Shulman. 2008. The Asymmetrical Influence of Sex Dissimilarity in Distributive vs. Colocated Work Groups. *Organization Science* 19, 4 (July 2008), 581–593. https://doi.org/10.1287/orsc.1070.0324

[26] Ying-Yu Chen, Ziyue Li, Daniela Rosner, and Alexis Hiniker. 2019. Understanding Parents' Perspectives on Mealtime Technology. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 1, Article 5 (March 2019), 19 pages. https://doi.org/10.1145/3314392

[27] Marshini Chetty, Richard Banks, Richard Harper, Tim Regan, Abigail Sellen, Christos Gkantsidis, Thomas Karagiannis, and Peter Key. 2010. Who's Hogging the Bandwidth: The Consequences of Revealing the Invisible in the Home. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 659–668. https://doi.org/10.1145/1753326.1753423

[28] Jamal I. Daoud. 2017. Multicollinearity and Regression Analysis. *Journal of Physics: Conference Series* 949 (dec 2017), 012009. https://doi.org/10.1088/1742-6596/949/1/012009

[29] George Demiris, Brian K. Hensel, Marjorie Skubic, and Marilyn Rantz. 2008. Senior residents' perceived need of and preferences for "smart home" sensor technologies. *International Journal of Technology Assessment in Health Care* 24, 1 (2008), 120–124. https://doi.org/10.1017/S0266462307080154

[30] Joan Morris DiMicco, Katherine J. Hollenbach, Anna Pandolfo, and Walter Bender. 2007. The impact of increased awareness while face-to-face. *Human–Computer Interaction* 22, 1-2 (2007), 47–96. https://doi.org/10.1080/07370020701307781

[31] Alan Dix and Corina Sas. 2008. Public displays and private devices: A design space analysis. https://alandix.com/academic/papers/Dix-Sas-PDPD-2008/Dix-Sas-PDPD-2008.pdf

[32] Michael Doh, Laura I. Schmidt, Florian Herbolsheimer, Mario Jokisch, and Hans-Werner Wahl. 2015. Patterns of ICT Use among "Senior Technology Experts": The Role of Demographic Variables, Subjective Beliefs and Attitudes. In *Human Aspects of IT for the Aged Population. Design for Aging*, Jia Zhou and Gavriel Salvendy (Eds.). Springer International Publishing, Cham, 177–188. https://doi.org/10.1007/978-3-319-20892-3_18

[33] André Doucette. 2014. *Group reaching over digital tabletops with digital arm embodiments.* Ph.D. Dissertation. University of Saskatchewan. https://core.ac.uk/reader/226164395

[34] Andre Doucette, Carl Gutwin, Regan L. Mandryk, Miguel Nacenta, and Sunny Sharma. 2013. Sometimes When We Touch: How Arm Embodiments Change Reaching and Collaboration on Digital Tables. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work (CSCW '13)*. ACM, New York, NY, USA, 193–202. https://doi.org/10.1145/2441776.2441799

[35] Nicolas Ducheneaut, Robert J. Moore, Lora Oehlberg, James D. Thornton, and Eric Nickell. 2008. Social TV: Designing for Distributed, Sociable Television Viewing. *Intl. Journal of Human–Computer Interaction* 24, 2 (2008), 136–154. https://doi.org/10.1080/10447310701821426

[36] Thomas Erickson and Wendy A. Kellogg. 2000. Social Translucence: An Approach to Designing Systems That Support Social Processes. *ACM Trans. Comput.-Hum. Interact.* 7, 1 (March 2000), 59–83. https://doi.org/10.1145/344949.345004

[37] Jesus Favela, Marcela Rodriguez, Alfredo Preciado, and Víctor M. Gonzalez. 2004. Integrating context-aware public displays into a mobile hospital information system. *IEEE Transactions on Information Technology in Biomedicine* 8, 3 (2004), 279–286. https://doi.org/10.1109/TITB.2004.834391

[38] Steffen Fieuws, Geert Verbeke, and Geert Molenberghs. 2007. Random-effects models for multivariate repeated measures. *Statistical Methods in Medical Research* 16, 5 (2007), 387–397. https://doi.org/10.1177/0962280206075305

[39] Matthias Finke, Anthony Tang, Rock Leung, and Michael Blackstock. 2008. Lessons Learned: Game Design for Large Public Displays. In *Proceedings of the 3rd International Conference on Digital Interactive Media in Entertainment and Arts (DIMEA '08)*. ACM, New York, NY, USA, 26–33. https://doi.org/10.1145/1413634.1413644

[40] Rowanne Fleck, Yvonne Rogers, Nicola Yuill, Paul Marshall, Amanda Carr, Jochen Rick, and Victoria Bonnett. 2009. Actions Speak Loudly with Words: Unpacking Collaboration around the Table. In *Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces (ITS '09)*. ACM, New York, NY, USA, 189–196. https://doi.org/10.1145/1731903.1731939

[41] James Fogarty, Jennifer Lai, and Jim Christensen. 2004. Presence versus availability: the design and evaluation of a context-aware communication client. *International Journal of Human-Computer Studies* 61, 3 (2004), 299 – 317. https://doi.org/10.1016/j.ijhcs.2003.12.016

[42] Purwa Kishor Gaikwad, Chris Theodore Jayakumar, Eashan Tilve, Niraj Bohra, Wenfei Yu, and Maria Spichkova. 2019. Voice-activated solutions for agile retrospective sessions, In Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 23rd International Conference KES2019. *Procedia Computer Science* 159, 2414–2423. https://doi.org/10.1016/j.procs.2019.09.416

[43] Radhika Garg and Christopher Moreno. 2019. Understanding Motivators, Constraints, and Practices of Sharing Internet of Things. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 2, Article 44 (June 2019), 21 pages. https://doi.org/10.1145/3328915

[44] Christine Geeng and Franziska Roesner. 2019. Who's In Control? Interactions In Multi-User Smart Homes. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300498

[45] Erving Goffman. 1959. *The Presentation of Self in Everyday Life.* Doubleday Anchor Books, Garden City, New York, NY, USA. https://openlibrary.org/works/OL3282045W/The_presentation_of_self_in_everyday_life

[46] Jane Gruning. 2017. Models for Ownership: Implications for Long-Term Relationships to Objects. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '17)*. ACM, New York, NY, USA, 2607–2613. https://doi.org/10.1145/3027063.3053232

[47] Jane Gruning and Siân Lindley. 2016. Things We Own Together: Sharing Possessions at Home. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 1176–1186. https://doi.org/10.1145/2858036.2858154

[48] Jacek Gwizdka. 2000. What's in the context? (April 2000). https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.132.4110&rep=rep1&type=pdf Extended Position paper for CHI 2000 Workshop: The What, Who, Where, When, Why and How of Context-Awareness.

[49] Joseph F. Hair, William C. Black, Barry J. Babin, and Rolph E. Anderson. 2010. *Multivariate Data Analysis: A Global Perspective.* Vol. 7. Pearson Education, Upper Saddle River, N.J., USA.

[50] Tom Hargreaves, Charlie Wilson, and Richard Hauxwell-Baldwin. 2018. Learning to live in a smart home. *Building Research & Information* 46, 1 (2018), 127–139. https://doi.org/10.1080/09613218.2017.1286882

[51] Amanda Harris, Jochen Rick, Victoria Bonnett, Nicola Yuill, Rowanne Fleck, Paul Marshall, and Yvonne Rogers. 2009. Around the Table: Are Multiple-Touch Surfaces Better than Single-Touch for Children's Collaborative Interactions?. In *Proceedings of the 9th International Conference on Computer-Supported Collaborative Learning, CSCL 2009 (CSCL '09)*, Claire O'Malley, Daniel Suthers, Peter Reimann, and Angelique Dimitracopoulou (Eds.), Vol. 1. International Society of the Learning Sciences, Rhodes, Greece, 335–344. https://repository.isls.org//handle/1/2968

[52] Kirstie Hawkey, Melanie Kellar, Derek Reilly, Tara Whalen, and Kori M. Inkpen. 2005. The Proximity Factor: Impact of Distance on Co-Located Collaboration. In *Proceedings of the 2005 International ACM SIGGROUP Conference on Supporting Group Work (GROUP '05)*. ACM, New York, NY, USA, 31–40. https://doi.org/10.1145/1099203.1099209

[53] Viviane Herdel, Anastasia Kuzminykh, Andrea Hildebrandt, and Jessica R. Cauchard. 2021. Drone in Love: Emotional Perception of Facial Expressions on Flying Robots. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. ACM, New York, NY, USA, 20. https://doi.org/10.1145/3411764.3445495

[54] Steven E. Higgins, Emma Mercier, Elizabeth Burd, and Andrew Hatch. 2011. Multi-touch tables and the relationship with collaborative classroom pedagogies: A synthetic review. *International Journal of Computer-Supported Collaborative Learning* 6, 4 (2011), 515–538. https://doi.org/10.1007/s11412-011-9131-y

[55] Uta Hinrichs and Sheelagh Carpendale. 2011. Gestures in the Wild: Studying Multi-Touch Gesture Sequences on Interactive Tabletop Exhibits. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 3023–3032. https://doi.org/10.1145/1978942.1979391

[56] Carolien Hoogland. 2000. *Semi-private Zones as a Facilitator of Social Cohesion.* Master's thesis. Katholieke Universiteit Nijmegen.

[57] Eva Hornecker. 2008. "I don't understand it either, but it is cool" - visitor interactions with a multi-touch table in a museum. In *2008 3rd IEEE International Workshop on Horizontal Interactive Human Computer Systems*. IEEE, Amsterdam, Netherlands, 113–120. https://doi.org/10.1109/TABLETOP.2008.4660193

[58] Eric Horvitz. 1999. Principles of Mixed-Initiative User Interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '99)*. ACM, New York, NY, USA, 159–166. https://doi.org/10.1145/302979.303030

[59] Elaine M. Huang and Elizabeth D. Mynatt. 2003. Semi-Public Displays for Small, Co-Located Groups. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '03)*. ACM, New York, NY, USA, 49–56. https://doi.org/10.1145/642611.642622

[60] Shahram Izadi, Harry Brignull, Tom Rodden, Yvonne Rogers, and Mia Underwood. 2003. Dynamo: A Public Interactive Surface Supporting the Cooperative Sharing and Exchange of Media. In *Proceedings of the 16th Annual ACM Symposium*

on User Interface Software and Technology (UIST '03). ACM, New York, NY, USA, 159–168. https://doi.org/10.1145/964696.964714
[61] Maia Jacobs, Henriette Cramer, and Louise Barkhuus. 2016. Caring About Sharing: Couples' Practices in Single User Device Access. In *Proceedings of the 19th International Conference on Supporting Group Work (GROUP '16)*. ACM, New York, NY, USA, 235–243. https://doi.org/10.1145/2957276.2957296
[62] William Jang, Adil Chhabra, and Aarathi Prasad. 2017. Enabling Multi-User Controls in Smart Home Devices. In *Proceedings of the 2017 Workshop on Internet of Things Security and Privacy (IoTS&P '17)*. ACM, New York, NY, USA, 49–54. https://doi.org/10.1145/3139937.3139941
[63] Alisa Kalegina, Grace Schroeder, Aidan Allchin, Keara Berlin, and Maya Cakmak. 2018. Characterizing the Design Space of Rendered Robot Faces. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction (HRI '18)*. ACM, New York, NY, USA, 96–104. https://doi.org/10.1145/3171221.3171286
[64] Amy K. Karlson, A.J. Bernheim Brush, and Stuart Schechter. 2009. Can I Borrow Your Phone? Understanding Concerns When Sharing Mobile Phones. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 1647–1650. https://doi.org/10.1145/1518701.1518953
[65] Joseph 'Jofish' Kaye. 2011. Self-Reported Password Sharing Strategies. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 2619–2622. https://doi.org/10.1145/1978942.1979324
[66] Peter H. Kim. 1997. When what you KnowCanHurt you: A study of experiential effects on group discussion and performance. *Organizational Behavior and Human Decision Processes* 69, 2 (1997), 165–177. https://doi.org/10.1006/obhd.1997.2680
[67] Anastasia Kuzminykh and Jessica R. Cauchard. 2020. Be Mine: Contextualization of Ownership Research in HCI. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (CHI EA '20)*. ACM, New York, NY, USA, 1–9. https://doi.org/10.1145/3334480.3383058
[68] Anastasia Kuzminykh and Edward Lank. 2019. How Much is Too Much? Understanding the Information Needs of Parents of Young Children. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 2, Article 52 (June 2019), 21 pages. https://doi.org/10.1145/3328923
[69] Airi M. I. Lampinen. 2014. Account Sharing in the Context of Networked Hospitality Exchange. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '14)*. ACM, New York, NY, USA, 499–504. https://doi.org/10.1145/2531602.2531665
[70] Jonas Landgren. 2005. Shared use of information technology in emergency response work: Results from a field experiment. In *Proc. of ISCRAM 2005 – 2nd International Conference on Information Systems for Crisis Response and Management*, B. Carle B. Van de Walle (Ed.). Royal Flemish Academy of Belgium, Viktoria Institute, Sweden, 35–41.
[71] Patricia G. Lange. 2007. Publicly private and privately public: Social networking on YouTube. *Journal of Computer-Mediated Communication* 13, 1 (2007), 361–380. https://doi.org/10.1111/j.1083-6101.2007.00400.x
[72] Ida Larsen-Ledet and Henrik Korsgaard. 2019. Territorial Functioning in Collaborative Writing. *Computer Supported Cooperative Work (CSCW)* 28, 3 (may 2019), 391–433. https://doi.org/10.1007/S10606-019-09359-8
[73] Josephine Lau, Benjamin Zimmerman, and Florian Schaub. 2018. "Alexa, Stop Recording": Mismatches between Smart Speaker Privacy Controls and User Needs. Poster presented at the 14th Symposium on Usable Privacy and Security (SOUPS 2018).
[74] Sunok Lee, Minji Cho, and Sangsu Lee. 2020. What If Conversational Agents Became Invisible? Comparing Users' Mental Models According to Physical Entity of AI Speaker. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 4, 3, Article 88 (Sept. 2020), 24 pages. https://doi.org/10.1145/3411840
[75] Ewa Luger and Abigail Sellen. 2016. "Like Having a Really Bad PA": The Gulf between User Expectation and Experience of Conversational Agents. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 5286–5297. https://doi.org/10.1145/2858036.2858288
[76] Paul Marshall, Rowanne Fleck, Amanda Harris, Jochen Rick, Eva Hornecker, Yvonne Rogers, Nicola Yuill, and Nick Sheep Dalton. 2009. Fighting for Control: Children's Embodied Interactions When Using Physical and Digital Representations. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 2149–2152. https://doi.org/10.1145/1518701.1519027
[77] Paul Marshall, Richard Morris, Yvonne Rogers, Stefan Kreitmayer, and Matt Davies. 2011. Rethinking 'Multi-User': An in-the-Wild Study of How Groups Approach a Walk-up-and-Use Tabletop Interface. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 3033–3042. https://doi.org/10.1145/1978942.1979392
[78] Roberto Martinez-Maldonado, Katerina Mangaroska, Jurgen Schulte, Doug Elliott, Carmen Axisa, and Simon Buckingham Shum. 2020. Teacher Tracking with Integrity: What Indoor Positioning Can Reveal About Instructional Proxemics. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 4, 1, Article 22 (March 2020), 27 pages. https://doi.org/10.1145/3381017

[79] Maya B. Mathur and David B. Reichling. 2016. Navigating a social world with robot partners: A quantitative cartography of the Uncanny Valley. *Cognition* 146 (2016), 22 – 32. https://doi.org/10.1016/j.cognition.2015.09.008

[80] Tara Matthews, Kerwell Liao, Anna Turner, Marianne Berkovich, Robert Reeder, and Sunny Consolvo. 2016. "She'll just grab any device that's closer" A Study of Everyday Device & Account Sharing in Households. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 5921–5932. https://doi.org/10.1145/2858036.2858051

[81] Tara Matthews, Kerwell Liao, Anna Turner, Marianne Berkovich, Robert Reeder, and Sunny Consolvo. 2016. "She'll Just Grab Any Device That's Closer": A Study of Everyday Device & Account Sharing in Households. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 5921–5932. https://doi.org/10.1145/2858036.2858051

[82] Michelle L. Mazurek, J. P. Arsenault, Joanna Bresee, Nitin Gupta, Iulia Ion, Christina Johns, Daniel Lee, Yuan Liang, Jenny Olsen, Brandon Salmon, Richard Shay, Kami Vaniea, Lujo Bauer, Lorrie Faith Cranor, Gregory R. Ganger, and Michael K. Reiter. 2010. Access Control for Home Data Sharing: Attitudes, Needs and Practices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 645–654. https://doi.org/10.1145/1753326.1753421

[83] Mark McGill, John Williamson, and Stephen A. Brewster. 2014. How to Lose Friends & Alienate People: Sharing Control of a Single-User TV System. In *Proceedings of the ACM International Conference on Interactive Experiences for TV and Online Video (TVX '14)*. ACM, New York, NY, USA, 147–154. https://doi.org/10.1145/2602299.2602318

[84] Mark McGill, John H. Williamson, and Stephen A. Brewster. 2015. A review of collocated multi-user TV. *Personal and Ubiquitous Computing* 19, 5-6 (2015), 743–759. https://doi.org/10.1007/s00779-015-0860-1

[85] Sugata Mitra. 2000. Minimally invasive education for mass computer literacy. Conference on Research in Distance and Adult Learning in Asia (CRIDALA 2000).

[86] Meredith Ringel Morris, Kathy Ryall, Chia Shen, Clifton Forlines, and Frederic Vernier. 2004. Beyond "Social Protocols": Multi-User Coordination Policies for Co-Located Groupware. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work (CSCW '04)*. ACM, New York, NY, USA, 262–265. https://doi.org/10.1145/1031607.1031648

[87] Souheila Moussalli and Walcir Cardoso. 2020. Intelligent personal assistants: can they understand and be understood by accented L2 learners? *Computer Assisted Language Learning* 33, 8 (2020), 865–890. https://doi.org/10.1080/09588221.2019.1595664

[88] Bonnie M. Muir. 1987. Trust between humans and machines, and the design of decision aids. *International Journal of Man-Machine Studies* 27, 5 (1987), 527–539. https://doi.org/10.1016/S0020-7373(87)80013-5

[89] Hendrik Müller, Jennifer Gove, and John Webb. 2012. Understanding Tablet Use: A Multi-Method Exploration. In *Proc. of the 14th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '12)*. ACM, New York, NY, USA, 1–10. https://doi.org/10.1145/2371574.2371576

[90] Miguel A. Muñoz, Victor M. Gonzalez, Marcela Rodríguez, and Jesus Favela. 2003. Supporting Context-Aware Collaboration in a Hospital: An Ethnographic Informed Design. In *Groupware: Design, Implementation, and Use*, Jesús Favela and Dominique Decouchant (Eds.). Springer Berlin Heidelberg, Berlin, Germany, 330–344. https://doi.org/10.1007/978-3-540-39850-9_28

[91] Miguel A. Nacenta, David Pinelle, Dane Stuckel, and Carl Gutwin. 2007. The Effects of Interaction Technique on Coordination in Tabletop Groupware. In *Proceedings of Graphics Interface 2007 (GI '07)*. ACM, New York, NY, USA, 191–198. https://doi.org/10.1145/1268517.1268550

[92] Kris Nagel, Cory D. Kidd, Thomas O'Connell, Anind Dey, and Gregory D. Abowd. 2001. The Family Intercom: Developing a Context-Aware Audio Communication System. In *Ubicomp 2001: Ubiquitous Computing*, Gregory D. Abowd, Barry Brumitt, and Steven Shafer (Eds.). Springer Berlin Heidelberg, Berlin, Germany, 176–183. https://doi.org/10.1007/3-540-45427-6_14

[93] Xudong Ni, Zhimin Yang, Xiaole Bai, Adam C. Champion, and Dong Xuan. 2009. DiffUser: Differentiated user access control on smartphones. In *2009 IEEE 6th International Conference on Mobile Adhoc and Sensor Systems*. IEEE, Los Alamitos, CA, USA, 1012–1017. https://doi.org/10.1109/MOBHOC.2009.5337017

[94] Karin Niemantsverdriet, Mendel Broekhuijsen, Harm van Essen, and Berry Eggen. 2016. Designing for Multi-User Interaction in the Home Environment: Implementing Social Translucence. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems (DIS '16)*. ACM, New York, NY, USA, 1303–1314. https://doi.org/10.1145/2901790.2901808

[95] Karin Niemantsverdriet, Harm van Essen, and Berry Eggen. 2017. A perspective on multi-user interaction design based on an understanding of domestic lighting conflicts. *Personal and Ubiquitous Computing* 21, 2 (2017), 371–389. https://doi.org/10.1007/s00779-016-0998-5

[96] Mark O'Connor, Dan Cosley, Joseph A. Konstan, and John Riedl. 2001. PolyLens: A Recommender System for Groups of Users. In *ECSCW 2001: Proceedings of the Seventh European Conference on Computer Supported Cooperative Work*, Wolfgang Prinz, Matthias Jarke, Yvonne Rogers, Kjeld Schmidt, and Volker Wulf (Eds.). Springer Netherlands, Dordrecht, Netherlands, 199–218. https://doi.org/10.1007/0-306-48019-0_11

[97] Kenton O'Hara, Matthew Lipson, Marcel Jansen, Axel Unger, Huw Jeffries, and Peter Macer. 2004. Jukola: Democratic Music Choice in a Public Space. In *Proceedings of the 5th Conference on Designing Interactive Systems: Processes, Practices, Methods, and Techniques (DIS '04)*. ACM, New York, NY, USA, 145–154. https://doi.org/10.1145/1013115.1013136

[98] Elizabeth Levy Paluck and Hana Shepherd. 2012. The salience of social referents: A field experiment on collective norms and harassment behavior in a school social network. *Journal of Personality and Social Psychology* 103, 6 (2012), 899–915. https://doi.org/10.1037/a0030015

[99] Zizi Papacharissi. 2009. The virtual geographies of social networks: a comparative analysis of Facebook, LinkedIn and ASmallWorld. *New media & society* 11, 1-2 (2009), 199–220. https://doi.org/10.1177/1461444808099577

[100] Konstantinos Papangelis, Melvin Metzger, Yiyeng Sheng, Hai-Ning Liang, Alan Chamberlain, and Ting Cao. 2017. Conquering the City: Understanding Perceptions of Mobility and Human Territoriality in Location-Based Mobile Games. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 90 (Sept. 2017), 24 pages. https://doi.org/10.1145/3130955

[101] Seonwook Park, Christoph Gebhardt, Roman Rädle, Anna Maria Feit, Hana Vrzakova, Niraj Ramesh Dayama, Hui-Shyong Yeo, Clemens N. Klokmose, Aaron Quigley, Antti Oulasvirta, and Otmar Hilliges. 2018. AdaM: Adapting Multi-User Interfaces for Collaborative Environments in Real-Time. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, 1–14. https://doi.org/10.1145/3173574.3173758

[102] Peter Peltonen, Esko Kurvinen, Antti Salovaara, Giulio Jacucci, Tommi Ilmonen, John Evans, Antti Oulasvirta, and Petri Saarikko. 2008. It's Mine, Don't Touch! Interactions at a Large Multi-Touch Display in a City Centre. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*. ACM, New York, NY, USA, 1285–1294. https://doi.org/10.1145/1357054.1357255

[103] Henning Pohl and Roderick Murray-Smith. 2013. Focused and Casual Interactions: Allowing Users to Vary Their Level of Engagement. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 2223–2232. https://doi.org/10.1145/2470654.2481307

[104] Martin Porcheron, Joel E. Fischer, Moira McGregor, Barry Brown, Ewa Luger, Heloisa Candello, and Kenton O'Hara. 2017. Talking with Conversational Agents in Collaborative Action. In *Companion of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17 Companion)*. ACM, New York, NY, USA, 431–436. https://doi.org/10.1145/3022198.3022666

[105] Martin Porcheron, Joel E. Fischer, Stuart Reeves, and Sarah Sharples. 2018. Voice Interfaces in Everyday Life. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3174214

[106] Martin Porcheron, Joel E. Fischer, and Sarah Sharples. 2017. "Do Animals Have Accents?": Talking with Agents in Multi-Party Conversation. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*. ACM, New York, NY, USA, 207–219. https://doi.org/10.1145/2998181.2998298

[107] Paul Prekop and Mark Burnett. 2003. Activities, context and ubiquitous computing. *Computer Communications* 26, 11 (2003), 1168–1176. https://doi.org/10.1016/S0140-3664(02)00251-7

[108] Brian E. Premo and William B. Stiles. 1983. Familiarity in verbal interactions of married couples versus strangers. *Journal of Social and Clinical Psychology* 1, 3 (1983), 209–230. https://doi.org/10.1521/jscp.1983.1.3.209

[109] Claire Rabin, Yona Bressler, and Edward Prager. 1993. Caregiver burden and personal authority: Differentiation and connection in caring for an elderly parent. *American Journal of Family Therapy* 21, 1 (1993), 27–39. https://doi.org/10.1080/01926189308250993

[110] Marie Ragert, Tim Schroeder, and Peter E. Keller. 2013. Knowing too little or too much: the effects of familiarity with a co-performer's part on interpersonal coordination in musical ensembles. *Frontiers in Psychology* 4 (2013), 368. https://doi.org/10.3389/fpsyg.2013.00368

[111] Simon Robinson, Jennifer Pearson, Shashank Ahire, Rini Ahirwar, Bhakti Bhikne, Nimish Maravi, and Matt Jones. 2018. *Revisiting "Hole in the Wall" Computing: Private Smart Speakers and Public Slum Settings.* ACM, New York, NY, USA, 1–11. https://doi.org/10.1145/3173574.3174072

[112] Daniel M. Russell, Clemens Drews, and Alison Sue. 2002. Social Aspects of Using Large Public Interactive Displays for Collaboration. In *Proceedings of the 4th International Conference on Ubiquitous Computing (UbiComp '02)*. Springer-Verlag, Berlin, Germany, 229–236. https://doi.org/10.1007/3-540-45809-3_18

[113] Kathy Ryall, Clifton Forlines, Chia Shen, and Meredith Ringel Morris. 2004. Exploring the Effects of Group Size and Table Size on Interactions with Tabletop Shared-Display Groupware. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work (CSCW '04)*. ACM, New York, NY, USA, 284–293. https://doi.org/10.1145/1031607.1031654

[114] Niloufar Salehi, Andrew McCabe, Melissa Valentine, and Michael Bernstein. 2017. Huddler: Convening Stable and Familiar Crowd Teams Despite Unpredictable Availability. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*. ACM, New York, NY, USA, 1700–1713. https://doi.org/10.1145/2998181.2998300

[115] Ravi Sandhu. 1996. Roles versus Groups. In *Proceedings of the First ACM Workshop on Role-Based Access Control (RBAC '95)*. ACM, New York, NY, USA, 2. https://doi.org/10.1145/270152.270163

[116] Alex Sciuto, Arnita Saini, Jodi Forlizzi, and Jason I. Hong. 2018. "Hey Alexa, What's Up?": A Mixed-Methods Studies of In-Home Conversational Agent Usage. In *Proceedings of the 2018 Designing Interactive Systems Conference (DIS '18)*. ACM, New York, NY, USA, 857–868. https://doi.org/10.1145/3196709.3196772

[117] Stacey D. Scott, M. Sheelagh T. Carpendale, and Kori M. Inkpen. 2004. Territoriality in Collaborative Tabletop Workspaces. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work (CSCW '04)*. ACM, New York, NY, USA, 294–303. https://doi.org/10.1145/1031607.1031655

[118] Stacey D. Scott and Sheelagh Carpendale. 2010. Theory of Tabletop Territoriality. In *Tabletops - Horizontal Interactive Displays*, Christian Müller-Tomfelde (Ed.). Springer London, London, United Kingdom, 357–385. https://doi.org/10.1007/978-1-84996-113-4_15

[119] William Seymour, Reuben Binns, Petr Slovak, Max Van Kleek, and Nigel Shadbolt. 2020. Strangers in the Room: Unpacking Perceptions of 'Smartness' and Related Ethical Concerns in the Home. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference (DIS '20)*. ACM, New York, NY, USA, 841–854. https://doi.org/10.1145/3357236.3395501

[120] Amit Kumar Sikder, Leonardo Babun, Z. Berkay Celik, Abbas Acar, Hidayet Aksu, Patrick McDaniel, Engin Kirda, and A. Selcuk Uluagac. 2020. Kratos: Multi-User Multi-Device-Aware Access Control System for the Smart Home. In *Proceedings of the 13th ACM Conference on Security and Privacy in Wireless and Mobile Networks (WiSec '20)*. ACM, New York, NY, USA, 1–12. https://doi.org/10.1145/3395351.3399358

[121] Randall B. Smith, Ronald Hixon, and Bernard Horan. 2001. Supporting Flexible Roles in a Shared Space. In *Collaborative Virtual Environments*, Elizabeth F. Churchill, David N. Snowdon, and Alan J. Munro (Eds.). Springer London, London, United Kingdom, 160–176. https://doi.org/10.1007/978-1-4471-0685-2_9

[122] Emily Sun, Rodrigo de Oliveira, and Joshua Lewandowski. 2017. Challenges on the Journey to Co-Watching YouTube. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*. ACM, New York, NY, USA, 783–793. https://doi.org/10.1145/2998181.2998228

[123] Anthony Tang, Melanie Tory, Barry Po, Petra Neumann, and Sheelagh Carpendale. 2006. Collaborative Coupling over Tabletop Displays. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '06)*. ACM, New York, NY, USA, 1181–1190. https://doi.org/10.1145/1124772.1124950

[124] Lucia Terrenghi, Aaron Quigley, and Alan Dix. 2009. A Taxonomy for and Analysis of Multi-Person-Display Ecosystems. *Personal Ubiquitous Computing* 13, 8 (June 2009), 583–598. https://doi.org/10.1007/s00779-009-0244-5

[125] Jennifer Thom-Santelli, Dan R. Cosley, and Geri Gay. 2009. What's Mine is Mine: Territoriality in Collaborative Authoring. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 1481–1484. https://doi.org/10.1145/1518701.1518925

[126] Francois Toutain, Ahmed Bouabdallah, Radim Zemek, and Claude Daloz. 2011. Interpersonal context-aware communication services. *IEEE Communications Magazine* 49, 1 (2011), 68–74. https://doi.org/10.1109/MCOM.2011.5681018

[127] Milka Trajkova and Aqueasha Martin-Hammond. 2020. "Alexa is a Toy": Exploring Older Adults' Reasons for Using, Limiting, and Abandoning Echo. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. ACM, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376760

[128] Thomas van de Werff, Karin Niemantsverdriet, Harm van Essen, and Berry Eggen. 2017. Evaluating Interface Characteristics for Shared Lighting Systems in the Office Environment. In *Proceedings of the 2017 Conference on Designing Interactive Systems (DIS '17)*. ACM, New York, NY, USA, 209–220. https://doi.org/10.1145/3064663.3064749

[129] Davy Vanacken, Chris Raymaekers, Kris Luyten, and Karin Coninx. 2007. Focus+Roles: Socio-Organizational Conflict Resolution in Collaborative User Interfaces. In *Human-Computer Interaction. HCI Applications and Services*, Julie A. Jacko (Ed.). Springer Berlin Heidelberg, Berlin, Germany, 788–796. https://doi.org/10.1007/978-3-540-73111-5_88

[130] Viswanath Venkatesh and Michael G. Morris. 2000. Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior. *MIS Quarterly* 24, 1 (2000), 115–139. https://doi.org/10.2307/3250981

[131] Leena Ventä-Olkkonen, Netta Iivari, and Kari Kuutti. 2017. Digital Technologies in Everyday Environments: Zooming in and out to Children's and Their Families' Smart Device Practices with Public and Private Screens. In *Proceedings of the European Conference on Cognitive Ergonomics 2017 (ECCE 2017)*. ACM, New York, NY, USA, 129–136. https://doi.org/10.1145/3121283.3121302

[132] Giovanna N. Vilaza, Willem F. G. Haselager, André M. C. Campos, and Louis Vuurpijl. 2014. Using games to investigate sense of agency and attribution of responsibility. In *Proceedings of the 2014 Brazilian Symposium on Computer Games and Digital Entertainment (SBGames 2014 Culture Track)*. Porto Alegre, Brazil, 393–399. https://www.sbgames.org/sbgames2014/papers/culture/full/Cult_Full_Using%20games%20to%20investigate.pdf

[133] Daniel Vogel and Ravin Balakrishnan. 2004. Interactive Public Ambient Displays: Transitioning from Implicit to Explicit, Public to Personal, Interaction with Multiple Users. In *Proceedings of the 17th Annual ACM Symposium*

on User Interface Software and Technology (UIST '04). ACM, New York, NY, USA, 137–146. https://doi.org/10.1145/1029632.1029656

[134] Dakuo Wang, Haodan Tan, and Tun Lu. 2017. Why Users Do Not Want to Write Together When They Are Writing Together: Users' Rationales for Today's Collaborative Writing Practices. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW, Article 107 (Dec. 2017), 18 pages. https://doi.org/10.1145/3134742

[135] Weigang Wang. 1999. Team-and-Role-Based Organizational Context and Access Control for Cooperative Hypermedia Environments. In *Proceedings of the Tenth ACM Conference on Hypertext and Hypermedia: Returning to Our Diverse Roots: Returning to Our Diverse Roots*. ACM, New York, NY, USA, 37–46. https://doi.org/10.1145/294469.294480

[136] Rina R. Wehbe, Terence Dickson, Anastasia Kuzminykh, Lennart E. Nacke, and Edward Lank. 2020. Personal Space in Play: Physical and Digital Boundaries in Large-Display Cooperative and Competitive Games. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. ACM, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376319

[137] Amanda Williams, Eric Kabisch, and Paul Dourish. 2005. From Interaction to Participation: Configuring Space through Embodied Interaction. In *Proceedings of the 7th International Conference on Ubiquitous Computing (UbiComp'05)*. Springer-Verlag, Berlin, Germany, 287–304. https://doi.org/10.1007/11551201_17

[138] Doug Williams, Marian F. Ursu, Pablo Cesar, Karl Bergström, Ian Kegel, and Joshan Meenowa. 2009. An Emergent Role for TV in Social Communication. In *Proceedings of the 7th European Conference on Interactive TV and Video (EuroITV '09)*. ACM, New York, NY, USA, 19–28. https://doi.org/10.1145/1542084.1542088

[139] Kristin Williams, Rajitha Pulivarthy, Scott E. Hudson, and Jessica Hammer. 2019. Understanding Family Collaboration Around Lightweight Modification of Everyday Objects in the Home. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 185 (Nov. 2019), 24 pages. https://doi.org/10.1145/3359287

[140] Julie R. Williamson and John Williamson. 2014. Analysing Pedestrian Traffic Around Public Displays. In *Proceedings of The International Symposium on Pervasive Displays (PerDis '14)*. ACM, New York, NY, USA, 13–18. https://doi.org/10.1145/2611009.2611022

[141] Anna Wojciechowska, Jeremy Frey, Esther Mandelblum, Yair Amichai-Hamburger, and Jessica R. Cauchard. 2019. Designing Drones: Factors and Characteristics Influencing the Perception of Flying Robots. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 3, Article 111 (Sept. 2019), 19 pages. https://doi.org/10.1145/3351269

[142] Anna Xambó, Eva Hornecker, Paul Marshall, Sergi Jordà, Chris Dobbyn, and Robin Laney. 2017. Exploring Social Interaction With a Tangible Music Interface. *Interacting with Computers* 29, 2 (2017), 248–270. https://doi.org/10.1093/iwc/iww019

[143] Aaron Xl Shen, Matthew KO Lee, Christy MK Cheung, and Huaping Chen. 2010. Gender differences in intentional social action: we-intention to engage in social network-facilitated team collaboration. *Journal of Information Technology* 25, 2 (2010), 152–169. https://doi.org/10.1057/jit.2010.12

[144] Nicola Yuill and Yvonne Rogers. 2012. Mechanisms for Collaboration: A Design and Evaluation Framework for Multi-User Interfaces. *ACM Trans. Comput.-Hum. Interact.* 19, 1, Article 1 (May 2012), 25 pages. https://doi.org/10.1145/2147783.2147784

[145] Eric Zeng, Shrirang Mare, and Franziska Roesner. 2017. End User Security and Privacy Concerns with Smart Homes. In *Thirteenth Symposium on Usable Privacy and Security (SOUPS 2017)*. USENIX Association, Santa Clara, CA, USA, 65–80. https://www.usenix.org/conference/soups2017/technical-sessions/presentation/zeng

[146] Eric Zeng and Franziska Roesner. 2019. Understanding and Improving Security and Privacy in Multi-User Smart Homes: A Design Exploration and In-Home User Study. In *28th USENIX Security Symposium (USENIX Security 19)*. USENIX Association, Santa Clara, CA, 159–176. https://www.usenix.org/conference/usenixsecurity19/presentation/zeng

Received January 2021; revised April 2021; accepted May 2021