Informing family-centered design through a neurocognitive approach

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1 INTRODUCTION

The family home is an important place for meaningful interactions and families are slowly allowing artificial agents, such as digital voice assistants, to join them in this space. Digital voice assistants and vacuuming robots may, however, only be the beginning of a stream of artificial agents into the family home. This development raises the question of how artificial agents are perceived by humans and how they in turn impact family dynamics. While research has associated meaningful relationships with pets with social and emotional well-being [30], little is known about the long-term effects of living with artificial agents. To bridge this knowledge gap, we propose an interdisciplinary approach that combines psychology, neuroscience, and human-ai interaction and views social dynamics of families through a neurocognitive lens. Here, we highlight the promise of this approach for family-centered design.

We propose that -rather than looking at interactions of family members in isolation- it is essential to consider families as complex social systems with interdependent members [2]. This acknowledges that to understand the perception and interaction with artificial agents and the impact on dynamics within families, we need methodologies that can capture the system level. The strength of the neurocognitive approach we propose is that it not only includes subjective measures (e.g., questionnaires), but also more objective measures (e.g., brain activity), explicit and implicit measures, and peals apart multiple layers of the interaction (i.e., brain and behaviour) and allows to measure multiple individuals simultaneously. This approach can provide insight into effects and mechanisms thereby both delivering fundamental knowledge on family life as well as novel input into the development of new artificial agents with the ultimate goal of promoting family well-being.

2 LEVERAGING MOBILE NEUROIMAGING TO UNDERSTAND FAMILY DYNAMICS AND INFORMING FAMILY-CENTERED DESIGN

Over the last years, attempts have been made to describe how individuals [4] or arbitrary groups [28] interact with artificial agents. These studies describe how expectations, beliefs, and perception at the level of the individual influence ongoing interactions [10]. However, these studies focus on laboratory measures and do not provide a mechanistic understanding of how these new interactions influence attitudes and behaviours of the entire social system in real life situations. Recent interview with a small number of families [6] point towards a complex interplay between behaviour of family members and the impact of an artificial agent. A systematic and theory-driven evaluation is needed. Successful artificial agents not only need to work for one user but are embedded in a social system and respond to multiple users. Via perpetual communication they can affect the entire households, their primary target group. They communicate information and social cues, capture attention and can fulfil members' cognitive and social needs [18]. We can only know the impact of these agents on social dynamics, when we know what individual members think, feel, and do in the social context of a family and how these individual minds influence each other.

In our research we take a neurocognitive approach and we extend beyond merely using self-report and behavioural measures and include neuroimaging to assess brain activity. This approach aims to investigate the neural basis of cognitive processes, such as emotion and social decision-making [29], and allows us to measure behavioural and neural changes in family dynamics in response to artificial agents. That way, mobile neurocognitive methods allow us to measure adults and young children in a standardized, objective manner which is especially valuable when conducting inter-generational research [20]. Neurocognitive measures can offer insights into underlying processes that might not be captured through explicit self-report or behavioural measures due to limited verbal abilities (e.g. of younger children), social desirability, or unawareness of certain attitudes [9]. Previous studies employing neuroimaging techniques, have been able to successfully map individuals' response to artificial agents [10,11] and this approach has been successful in outline social dynamics of dyads [27] and non-family groups [31]. The next step is to understand the cognitive underpinnings of real-life interaction on a familial level. Brain-to-brain coupling, for example, allows us to identify shared patterns of brain activity by measuring two or more participants simultaneously [20]. In the past, this technique has been successfully used to relate neural coupling to social dynamics [5] and collective performance [25]. Within the family home, neural activation patterns across family members may, for example, reveal implicit power dynamics, such as follower-leader relationships during family interactions that may not be detected through purely behavioural research [15].

In the past, neurocognitive research has, however, often been limited by its stationarity, requiring participants to be tested in an artificial laboratory setting and limiting natural interactions between multiple participants. This research often falls short in terms of ecological validity, as a most real-life interactions between family members take place in their home. Fortunately, the recent rise of mobile neuroimaging techniques offers new possibilities for using the neurocognitive approach in the context of family research. Importantly, this technology can now be used wirelessly, and it is relatively tolerant to motion artifacts, allowing for natural interactions [23]. This makes it possible to study unconstrained human-robot interactions between multiple participants inside the family home [8] leading to high ecological validity and data quality [16]. Mobile neuroimaging techniques do not require families to travel to the laboratory and have minimal sample exclusion criteria, making it possible to test children across various age groups and allowing us to test diverse family structures [23].

The approach we take is informed by the cognition in the wild approach spearheaded by the fields of anthropology and biology [12], which shows that an individual's behaviour and cognition during a task measured in a laboratory does not reflect the behavioural and cognition in the natural environment of the individual [21,24]. A neurocognition in the wild approach will help capture the complexity and diversity of social behaviour and providing a richer explanation of underlying mechanisms [13]. Behaviour and brain processes of social dynamics can only be truly understood when investigated in a situational context at home. This approach will allow to measure true behaviour in real-world situations, improve data quality [1,3], and ultimately lead to generalisable theories on human behaviour that extend beyond laboratory-based theories [17,22].

Looking into the future, the neurocognitive approach can be used to further improve families' interaction with artificial agents. In a society that gets increasingly older, artificial agents will ideally soon engage in care activities in the family home. A necessary application of the neurocognitive approach will then be to inform us how to build improved artificial agents that are easily integrated into family homes. It is therefore important to know how artificial agents are perceived and which changes in their appearance or response style affect our perception of them. Neurocognitive research has already show that activation during engagements with robots can also activate object-specific brain regions [8] and that not only human-likeness but also perceived socialness shape brain activity during interactions with robots [14]. When artificial agents take over those sensitive tasks, we may not only consider how they look, but also how they are perceived by the user [10]. In the future, for instance, we may use this method to increase perceived socialness instead of human-likeness of artificial agents to create ideal circumstances for human-robot households [14]. Overall, this approach will provide us a more nuanced and objective understanding of human-robot interaction within familial settings, ultimately improving the integration of artificial agents into the family home.

3 REMAINING CHALLENGES AND FUTURE COLLABORATION

Despite the possible advantages of using the neurocognitive approach, challenges and questions remain (Table 1). Firstly, the process of setting up the neurocognitive installations can be quite time-consuming, involving numerous repetitions that can lead to boredom, especially among children. Children might also feel tense while wearing a neuroimaging device and their sudden movements might introduce noise, posing an additional challenge in data interpretation and analysis. Furthermore, studying neural synchrony requires researchers to implement a meaningful control task to correct for the effects of, for example, a shared environment [7]. Another challenge that arises is the case of discrepant results between the data collected with self-report and those collected with neuroimaging or behavioural measures. The dilemma lies in determining which data holds greater significance for designing artificial agents ensuring the well-being of the families.

These challenges show that while the neurocognitive approach offers a fresh perspective on family studies, it should be complemented by other disciplines, enriching the overall understanding of family dynamics and interactions. For instance, collaboration with computer science is vital to improve robots' behavioural patterns according to how it is perceived by the users. Partnering with developmental and family psychology is crucial to account for developmental factors like brain maturation. The neurocognitive approach will therefore reach its full potential in collaboration with other fields. By integrating neurocognition with perspectives from diverse disciplines we can enhance our understanding of family dynamics and improve family-centered designs.

Table 1: Remaining questions for the workshop

Question	Challenge
What methods can we employ to address age-related differences in children's interactions with AI?	It is reasonable to expect that a twelve-year-old would engage more extensively with a digital voice assistant compared to a four-year-old
How do we design tasks that are suitable for all age groups?	Traditional decision tasks, such as an economic game like the trust game, may not be appropriate for young children. Fortunately, more and more child-friendly tasks are available [19,26]. Child-friendly adaptations are, however, rare and often not computer-based, making data analysis challenging. In return, the child-friendly versions of those tasks may fail to engage adult family members and affect their decision-making.
How do we use self-report in children who cannot read or write?	Having a researcher or parent present while answering self-report questions may introduce social desirability bias and systematically affect the data obtained in families. Relying solely on images for children's self-reporting may be limiting.
What reference category can we use for studying artificial agents in the family context [8]?	Often, robotic agents are compared to human agents, but this might not be the best reference category. To provide a well-controlled and nuanced assessment, results need to be compared across a wide variety of households with or without artificial agents.

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