Transactive Memory in Caregiver Networks Using Artificial Intelligence

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Abstract

As the population ages and an increasing number of adults want to age in place in their homes, they will rely on a network of family, friends, and other caregivers to provide various forms of assistance. Coordination across this loosely connected network is a common challenge, requiring information sharing, schedule alignment and task coordination. Here, we propose that artificial intelligence (AI) may be used to develop tools to help loosely connected care networks develop better collective cognition. Specifically, we focus on helping members of care networks develop a transactive memory system, or a shared system for storing and retrieving knowledge that expands the capacity of a group to effectively use information. In this paper, we describe the motivation for our study, and our planned research program based on the use of an online experimental platform facilitating human-AI collaboration to develop and test tools to enhance collective cognition in care networks.

Introduction

The average age of the world population has been projected to continue to rise steeply through the rest of this century (Lutz et al. 2008) with almost 40% of the population in the US over age 60 by the year 2100 (Tuljapurkar et al. 2000). As the amount and type of assistance needed increases for most adults as they age, older adults increasingly rely on family and friends for help. Today, over 53 million Americans are estimated to be caregivers to a family member marking a significant increase over the last few decades (Binette et al. 2021).

When caregiving responsibility falls primarily on one or a few family members, it can become physically and mentally taxing, underscoring the urgent need for support for these vital roles (Trivedi et al. 2014). However, the diverse range of needs of most older adults can be significant, including everything from daily check-ins and assistance with activities of daily living, such as bathing and eating, to managing complex interactions with the healthcare system (Peek et al. 1997) making coordination of many helpers quite complex. However, when a care network — or a loosely coupled group of family, friends, and/or paid caregivers — can be effectively coordinated, it can result in a significant positive impact on the daily lives and overall well-being of the recipients (O'Caoimh et al. 2016).

A core challenge of coordination in a care network is managing collective information, particularly helping members understand who knows what or who needs to know what. A survey and interview study involving 2,000 caregivers in the USA highlighted a variety of difficulties, including communication breakdowns, scheduling conflicts, and the management of caregiving responsibilities (Schurgin et al. 2021). Many caregivers reported challenges in getting information to the right people or ensuring coverage when care is needed and alignment on tasks. Furthermore, caregivers may understand their role and tasks, but lack knowledge of other caregivers' activities or important information that could affect the overall well-being of the care recipient (Li et al. 2023).

These challenges underscore the critical need for better systems to support the collective intelligence (CI) of care networks to enable them to effectively share information, coordinate tasks, and make informed decisions (Woolley et al. 2024). In this research program, we focus on the role of AI-enabled tools to support the collective cognition necessary for collective intelligence to emerge. Here we focus on tools to support the development of collective memory.

Transactive Memory Systems

An area where AI-enabled tools could be leveraged to enhance CI is in helping care networks develop a transactive memory system (TMS), or a dynamic system consisting of member's understanding of each others' knowledge and skills that facilitates allocation and retrieval of information to and from the most appropriate member (Argote et al.

2012). TMS develops via three transactive processes that maximize capacity for storing information and utilizing it effectively: updating, allocation, and retrieval. In traditional teams, whether co-located or distributed, learning and updating "who knows what" occurs as members cooperate to accomplish interdependent tasks and observe evidence of others' competencies. Allocation occurs as members direct new, incoming information to others who are most likely to use it and store it. This is enhanced by updating via ongoing experience, and expands the total useful information capacity of the network. Specialization develops as a consequence of the consistent allocation of new information within a particular domain to the same member (and information from other domains to other members). Retrieval is, in turn, enhanced as members direct inquiries in certain domains to the associated member, which minimizes the time required for retrieving knowledge. By reliably and successfully responding to others' inquiries in a knowledge domain, each member establishes credibility with the others and solidifies the network's shared beliefs about each member's expertise.

Research on TMS was initially conducted with co-located team members, but a growing number of studies demonstrate its benefits in distributed and virtual teams, working synchronously or asynchronously (Yan et al. 2021). Technology can facilitate TMS developments, particularly when used to facilitate communication, but when tools are used as substitutes for human cognition to store directory information about who knows what, it can undermine team effectiveness (Gupta et al. 2018).

The rapid advancement of AI tools, particularly in understanding, recording, and retrieving relevant communication, offers significant potential to enhance the coordination of home care networks by assisting them in developing a transactive memory system (Faraj et al. 2019). By utilizing natural language comprehension and generation technologies such as large language models (LLMs), AI could stimulate information seeking and sharing among care network members that serve as the engine of TMS, and potentially avoid the downsides of supplanting the development of shared cognition that occurs if technology is used to simply store the information (Sparrow et al. 2011). Facilitating TMS development would supply one of the key components identified by the Transactive Systems Theory of Collective Intelligence as essential for developing collective intelligence in many settings, including healthcare (Gupta et al., 2021).

Here we describe an approach to leveraging AI more generally in the context of full-cycle research (Chatman et al. 2005), which enables researchers to triangulate between direct observation of phenomena and more controlled experimentation to refine their understanding and, in our case, test tools that will robustly support the forms of collective cognition that we know can enhance team coordination.

Full Cycle Research

Full-cycle research is a dynamic and iterative approach to scientific inquiry that emphasizes the continuous interplay between field observation, theory development, and experimental testing (Chatman et al. 2005). The approach is novel in the context of academic research, where qualitative and experimental methodologies are typically siloed and conducted within different subdisciplines of a field (if not in different disciplines) and published for different audiences. Over time, multi-method approaches or comprehensive reviews might connect and cross-pollinate ideas, though development typically follows a linear progression from more qualitative and exploratory to more focused and quantitative methods, with application to real-world problems as an afterthought.

By contrast, full-cycle research advocates for a cyclical process where insights from natural settings inform theoretical models, which are then rigorously tested in controlled environments, such as experiments, and subsequently validated back in the field. This approach ensures that research findings are not only theoretically sound but also practically relevant, offering a comprehensive understanding of complex phenomena. Such an approach parallels widely used model in software development and product management, such as the V-Model, which proceeds from design (rooted in understanding requirements), to implementation (where code is rigorously tested), and then to integration (where the resulting software is tested by users to ensure it meets requirements.) What is novel about full-cycle research is its application to the development and application of scientific theories, often involving a variety of scientists in different subfields or disciplines, and their application to real-world problems. A contribution of this research program is the application of full cycle research in the context of application-oriented multidisciplinary collaboration, where real world use cases are combined with relevant theories to devise potential solutions that both advance the underlying science and its application.

By implementing full-cycle research in the development of AI-based tools for enhancing transactive memory systems (TMS) within care networks, we build from initial field observations and interviews with caregivers to provide the foundation for identifying key areas where TMS can be improved, particularly in managing the coordination required to help the elderly age in place. These insights inform the design of our AI-based tools, which are then tested in a controlled experiment for their impact on TMS development.

To conduct our controlled experiments, we developed the Collaborative Caring Virtual Testbed, a digital environment simulating a caregiving situation. In this testbed, participants are assigned roles as caregivers to care for a recipient with ongoing emergent needs. As they handle routine tasks,

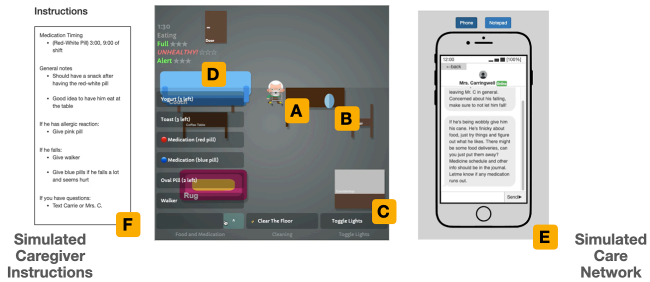

Figure 1. The main interface of the Collaborative Caring Virtual Testbed, featuring (a) a care recipient, (b) tasks such as medication management, (c) environmental objects, (d) optional status indicators, (e) a simulated interactive care network, and manipulatable caregiver instructions and tools.

diagnose unexpected problems, and address them, they consult notes and information provided by other members of the care network and reach out to them for assistance. Synthetic team members (implemented using adapted language models) are developed and tested to serve as facilitators of transactive memory system development among the members of the care network, allowing us to evolve effective app-based tools for future testing in field settings.

The cyclical nature of our research allows us to refine our tools continuously, ensuring they are adaptable to the evolving needs of different care situations. By moving back and forth between natural observations and controlled experiments, we can validate the efficacy of our interventions, ensuring they are robust, generalizable, and capable of producing tangible improvements in care network coordination. This iterative process not only enhances the practical applicability of our tools but also contributes to the theoretical understanding of how TMS develops and how AI can facilitate collective cognition in complex social networks.

Large Language Models and TMS

Large Language Models (LLMs) can be instrumental in helping care networks develop a TMS. At the most basic level of AI support, ‘Content’ AI support can assist members of a care network in locating information and its association with other members to help all contributors build a shared understanding of who knows what. In addition, this Content AI support could proactively solicit information from the care network to ensure important details are made available to other members and consolidated to identify important new patterns or developing issues. Such a function can result in an important knowledge base that can be queried as problems emerge, and help build a shared understanding that adapts as the situation changes.

Another form of support for the care network is “Social AI Support,” which in addition to providing content can also serve to build and reinforce members’ understanding, credibility and trust of one another. Such an assistant would be cognizant of building members’ awareness of the source of information, prompting each other for mutual assistance as needed, and helping make contributions visible by communicating about them to the network.

Leveraging our understanding of TMS within teams, the provision of Content and Social AI Support could not only aid in the effective distribution of tasks and information but also ensure that all members are aligned with the current status and needs of the care recipient, thereby minimizing the risk of errors and enhancing the overall efficiency of the caregiving process. Such AI-enhanced tools could fundamentally improve how care network members communicate and collaborate, making the care process more seamless and less prone to the common pitfalls of miscommunication and task misalignment. Additionally, such support could help ‘bootstrap’ networks with member turnover or dynamic membership perform to the level of more mature, performant teams.

However, extending AI support beyond content and into social interaction has many potential risks, and exposes the system to rejection by the network participants if the resulting system interactions fail to be sufficiently useful or seamless. An important research question in this program examines a core assumption underlying the interaction between AI support, transactive memory support, and social interaction - can a sufficiently useful AI support system develop and reinforce team transactive memory by shepherding social interactions between team members? Does this approach maintain effectiveness over time or is it best used to ‘bootstrap’ TMS?

Proposed Method

We will conduct our study as a randomized, controlled online experiment utilizing the Collaborative Caring Virtual Testbed. In this testbed, participants are assigned roles as caregivers to a recipient with ongoing emergent needs. After a brief training module that introduces them to the platform, participants engage in a simulated caregiving shift. They are tasked with diagnosing and addressing the recipient's various needs to maintain their comfort and health. At the end of their shift, participants receive a performance evaluation based on an algorithm and then complete a survey to capture additional data on their experiences and perceptions before the experiment concludes.

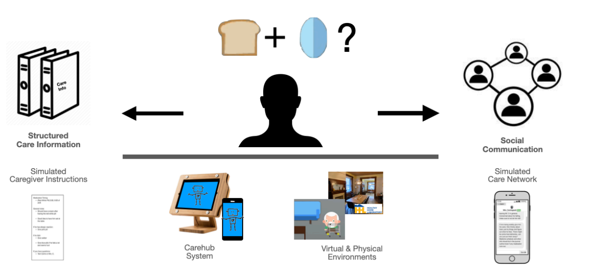

Figure 2. The Collaborative Care Virtual Testbed additionally lays the foundation for the evaluation of AI-support interventions for caregiving tasks in a diversity of form factors, environments, care network configurations, and levels of existing caregiver support.

Our research protocol has been approved by the Institutional Review Board (IRB) at Carnegie Mellon University.

Manipulations

The experiment differentiates participant experiences through three types of AI support, aiming to examine the impact of AI on caregiving coordination at three different levels. In the No AI Support condition, participants receive standard caregiving information via notes and messages, reflecting typical communication environments in asynchronous distributed work environments, including caregiving. The Content AI Support condition provides participants with an AI agent that summarizes and clarifies information aiding in understanding and retention. The Social AI Support condition enhances this further by having an AI agent help identify knowledgeable members within the social network and their connection to relevant information, helping to clarify task allocation and member relationships, enhancing overall network efficiency.

Measures

Our key dependent measure, transactive memory, will be captured both based on behavioral indicators (Riedl et al. 2021) as well as with validated survey measures (Lewis 2003). Behavioral measures will include the accuracy of information seeking, allocation, and retrieval by directing questions to the appropriate care network member or sharing critical information with those who should receive. These behavioral measures will be triangulated with participants' responses to validated self-report measures of transactive memory used in extant research (Lewis 2003). These questionnaires include items such as the degree to which participants knew what task-related skills and knowledge other care network members possess; who in the network had specialized skills and knowledge that was relevant to their work; and, whether others shared their special knowledge and expertise with one another.

Broader Impact Statement

This research program is in the conceptual stage, with the goal of progressing toward and iterating with usability testing as we triangulate theory and application. We conducted qualitative interviews with healthy older adults and caregivers of adults with MCI in the initial stages of this research to provide the basis for our experimental design. A main contribution of our work is the application of full-cycle research in the context of application-oriented multidisciplinary scientific collaboration, where real world use problems are addressed by relevant theories to devise potential solutions that advance both the underlying science and its application. The goal of this work is to support the development of AI-based tools that will facilitate the coordination of care networks to enable older adults to age in place by helping the community around them provide the assistance they need.

References

Argote, L., and Ren, Y. 2012. Transactive Memory Systems: A Microfoundation of Dynamic Capabilities. Journal of Management Studies 49(8): 1375–82. doi.org/10.1111/j.1467-6486.2012.01077.x.

Binette, J., and Farago, F. 2021. 2021 AARP Home and Community Preferences Survey: A National AARP Survey of U.S. Adults Age 18+. Washington, DC: AARP Research. doi.org/10.26419/res.00479.001.

Chatman, J. A., and Flynn, F. J. 2005. Full-Cycle Micro-Organizational Behavior Research. Organization Science 16(4): 434–47. doi.org/10.1287/orsc.1050.0136.

Gupta, P., and Woolley, A. W. 2018. Productivity in an Era of Multi-Teaming: The Role of Information Dashboards and Shared Cognition in Team Performance. In Proceedings of the 2018 ACM Conference on Computer-Supported Cooperative Work and Social Computing. New York: Association for Computing Machinery. doi.org/10.1145/3274331.

Lewis, K. 2003. Measuring Transactive Memory Systems in the Field: Scale Development and Validation. Journal of Applied Psychology 88(4): 587–604. doi.org/10.1037/0021-9010.88.4.587.

Li, L.; Arnold, V.; and Piper, A. M. 2023. Any Bit of Help, Helps: Understanding How Older Caregivers Use Carework Platforms for Caregiving Support. In Proceedings of the

2023 CHI Conference on Human Factors in Computing Systems. New York: Association for Computing Machinery. doi.org/10.1145/3544548.3580659.

Lutz, W.; Sanderson, W.; and Scherbov, S. 2008. The Coming Acceleration of Global Population Ageing. Nature 451(7179): 716–19. doi.org/10.1038/nature06516.

O'Caoimh, R.; Cornally, N.; Svendrovski, A.; Weathers, E.; FitzGerald, C.; Healy, E.; O'Connell, E.; O'Keeffe, G.; O'Herlihy, E.; and Gao, Y. 2016. Measuring the Effect of Carers on Patients' Risk of Adverse Healthcare Outcomes Using the Caregiver Network Score. Journal of Frailty and Aging 5(2): 104–10.

Sparrow, B.; Liu, J.; and Wegner, D. M. 2011. Google Effects on Memory: Cognitive Consequences of Having Information at Our Fingertips. Science 333(6043): 776–78. doi.org/10.1126/science.1207745.

Tuljapurkar, S.; Li, N.; and Boe, C. 2000. A Universal Pattern of Mortality Decline in the G7 Countries. Nature 405(6788): 789–92. doi.org/10.1038/35015561.

Woolley, A. W., and Gupta, P. 2024. Understanding Collective Intelligence: Investigating the Role of Collective Memory, Attention, and Reasoning Processes. Perspectives on Psychological Science 19(2): 344–54. doi.org/10.1177/17456916231191534.

Yan, B.; Hollingshead, A. B.; Alexander, K. S.; Cruz, I.; and Shaikh, S. J. 2021. Communication in Transactive Memory Systems: A Review and Multidimensional Network Perspective. Small Group Research 52(1): 3–32. doi.org/10.1177/1046496420967764.