Inferring cognitive impairment and adapting PIM systems using interaction patterns

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SHORT SUMMARY

In this position paper I argue for using human interactions with PIM tools to monitor and detect cognitive decline in order enable administration of preventative measures (external to the human-technology interaction, e.g., by medical personnel) and restorative measures (internal to the human-technology interaction, e.g., by having tools adapt themselves to a human).

POSITION PAPER

Population in most developed countries is aging, with aging population comes increase of age-related conditions such as mild cognitive impairment (MCI) and dementia. In 2020 in the USA 6 million people had Alzheimer's disease (AD) and 12 million people had MCI (Rajan et al., 2021). It is estimated that 15% people with MCI will develop dementia after only two years (Petersen et al., 2018), and 33% people with MCI develop AD within five years (Ward et al., 2013).

Evidence shows that detecting cognitive decline early is very important. An early diagnosis gives persons affected by cognitive decline time to prepare and enables administration of treatments and interventions. However, such detection is challenging. Typical cognitive tests (such as, Montreal Cognitive Assessment (MoCA), National Institute of Health (NIH) Toolbox Cognition, California Verbal Learning Test, Visual Object and Space Perception battery) are frequently paper-and-pencil, require trained personnel to administer them and may be expensive. Furthermore, recent research demonstrated that individuals not meeting the traditional criteria for MCI may be in a PreMCI state with a faster cognitive decline than among persons who are cognitively healthy (Crocco et al., 2018). There is pressing need to identify cognitive measures that are sensitive to PreMCI.

Therefore there are many efforts to find alternative ways of diagnosing early onset of cognitive impairments. National Institute on Aging (NIA, a part of National Institute of Health) leads many efforts[i] in this area, while other organizations have similar efforts underway. For example, NIH National Institute of Neurological Disorders and Stroke leads Consortium for Detecting Cognitive Impairment, Including Dementia (DetectCID[ii]); Center for Disease Control and Prevention's (CDC) Healthy Brain Initiative[iii] promotes advancing early detection to "Make Alzheimer's Our Next Public Health Success Story"[iv].

Some efforts sponsored by these organizations turn to multi-channel monitoring of everyday life activities at home. One promising example comes from data collected in EVALUATE-AD trial (Thomas et al., 2020). The results show advantage over occasional and episodic clinic-based assessments. This trial monitored home activity, medication-taking behavior, physiological data (weight), driving, computer use. However, monitoring most of these activities required specialized equipment. To increase feasibility and ecological validity one could consider collecting data on common computing devices, which are already present at home, such as computers, tablets and smartphones.

Computing technology use behaviors (including mouse and eye movement) were shown to be sensitive to cognitive changes in individuals with MCI and AD (Seelye et al., 2015; Stringer et al., 2018). However, tasks used in these studies were decontextualized and required special stimuli. For example, Bott and colleagues (Bott et al., 2017) used visual paired comparison tasks (VPCT). VPCT is a memory recognition task, which is based on a sequential presentation of already-seen/already-seen or already-seen/new image pairs. People without dementia look at new images longer than on already-seen images, while for people with dementia there is no such difference. Another example is anti-saccade task in which participant is asked to look in the opposite direction to the presented stimulus (Noorani, 2014). It is much harder for people with dementia to suppress direction of the presented stimulus.

While performance on these specialized tasks was successfully used to predict if a participant was an older adult with intact cognition or an older adult with MCI or AD, the need to use special apps for these purposely designed tasks limits usefulness of such approaches. Therefore there is a need to investigate how age-related cognitive changes manifest in ecologically-valid tasks in which people are interacting with everyday computing devices.

I suggest to use interactions with PIM tools (or more broadly computing devices) to monitor and detect cognitive decline in order enable administration of preventative measures (external to the human-technology interaction, e.g., by medical personnel) and restorative measures (internal to the human-technology interaction, e.g., by having design adapt itself to a human).

Interaction with PIM tools requires motor, perceptual, and cognitive skills, as we age most of these skills decline, and so our interactions with these tools will change. I propose that a person's interactions with PIM tools can be used to monitor these changes, with a particular focus on changes in cognitive skills in order to detect cognitive decline. The interactions (signals) could include touch/mouse movement, clicks, keystrokes (the text entered), and data from additional instruments (such as webcams / eye-tracking). The goal is to detect ("diagnose") cognitive impairment early to enable undertaking appropriate measures.

Cognitive abilities decline gradually with normal aging. For example, executive control and working memory capacity are in gradual decline since our twenties. On the positive side, research shows that the effects of cognitive decline (e.g., executive control and working memory (WM)) can be compensated. This could be achieved by, for example, strategy training and context reinstatement (Craik, 2005). Studies of information search show that even without introducing compensatory measures, older adults are not necessarily less accurate in finding information on the web. However, they tend to be slower and able to perform fewer searchers than young adults (Sharit et al., 2016).

A digression: I referred a few times to PIM tools and, more broadly, to computing devices. But that's not entirely a fair comparison. The "personal" character of information we manage in PIM tools is unique and different from (largely) "impersonal" information accessed by us through non-PIM software or apps. Personal information is strongly related to our episodic memories and that fact places it in a different category. In dementia we gradually loose our ability to remember recent events and the retention of recent episodes from our lives becomes harder and harder. Episodic memory is particularly disrupted in Alzheimer's disease (Tromp et al., 2015). Other types of computing tools (i.e. non-PIM tools) are not used to manage this type of information. Though, one should note that interactions with computing devices and apps become events in our lives in their own right, that is, interaction episodes can become part of the content of our episodic memories. Skilled interactions with these devices are mainly driven by procedural memory, which declines after episodic memory.

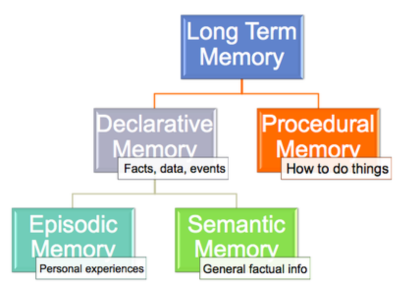

Fig 1. Endel Tulving's Long-Term Memory (LTM)

(Source: https://www.psychologywizard.net/tulvings-long-term-memory-ao1-ao2-ao3.html)

The results from prior research confirm that changes in cognition which affect human interaction with PIM tools and also inform us about the plausibility of compensating for cognitive decline. I propose to take advantage of this information to improve human interaction with PIM tools and prevent as well as compensate for decline in cognitive function.

Proposed plan (**M^{2}ERI**):

1. **Map**: Map PIM interaction tasks on cognitive resources required for their performance. This mapping should go beyond the traditional task analysis in HCI (e.g., Kieras, 2004), which typically does not consider the required cognitive resources in detail. The cognitive resources are used to explain human performance (or issues in the performance), but typically are not the focus of the analysis. Some domains may be an exception in their approach to task (user performance) analysis. For example, in decision making the information processing model explicitly includes attentional resources and memory (LTM, WM). The process of mapping should start with a thorough literature review (perhaps a systematic review).
2. **Measure**. Establish performance markers of MCI (and other levels of CI). Measure task performance of healthy and MCI older adults in relation to the required cognitive resources. Operationalize measures as interaction performance: 1. haptic: keypresses (timing), mouse movements (timing, location, trajectory), screen touches (similar to mouse movements), etc., 2. eye movement (timing and location of fixations, saccades and their dynamics), 3. semantic: content of the text entered (e.g., keywords, queries), etc. One of the biggest challenges will be how to handle individual differences, and, in particular, individual differences in cognitive abilities. At any point in their lives, people differ in cognitive abilities. People also differ in how their cognitive abilities change over time and in different contexts. It is possible that the performance markers (or ranges of their values) will need to be established separately for each individual. It is also possible that such systematic approach to establishing performance markers will not be possible and that we will need to establish general classes of interaction features for re-design / UI adaptation that help older adults (and especially older adults with CI).
3. **Evaluate**: Once the performance markers are established, evaluate and replicate them in additional empirical studies with different participant groups, in different contexts and over time.
4. **Refine**: Refine the performance markers based on empirical results. Perform steps 3 and 4 even if the systematic approach to establishing performance markers is not possible.
5. **Improve**: Design interfaces and interactions which will compensate for the decline in cognitive function. This may involve designing adaptive interfaces which will *measure* performance markers to adapt to older users, while supporting the same performance for younger users. We can expect that techniques such as "intelligent" autofill and autocorrection could reduce the number of keypresses required to enter text. Another possibility for text entry interfaces could be to take advantage of user vocabulary, since we know that vocabulary – an aspect of crystallized intelligence - improves with age.

> *A specific possibility to improve implicit memory (related to skilled performance of procedures) may be to implement a practical dementia care model such as Preserved Implicit Memory (PIM – sic!). In this approach preserved implicit memories are activated with perceptual priming of familiar objects and reinforcement of learned motor skill memories within tasks (Harrison et al., 2007).*

Externally to technology, performance markers will enable us to detect ("diagnose") cognitive impairment and thus to administer preventative measures to, possibly, slow down further progress of cognitive impairment and to make adjustments in the person's life. *Internally to technology*, performance markers will enable us to built adaptable and adaptive user interfaces that better suit older adults with CI.

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[i] https://www.nia.nih.gov/research/blog/2020/12/tools-earlier-detection-cognitive-impairment-and-dementia
[ii] https://www.detectcid.org/
[iii] https://www.cdc.gov/aging/healthybrain/
[iv] https://www.cdc.gov/aging/healthybrain/pdf/issue-map-early-detection-508.pdf