Embedded Assessment: Overcoming Barriers to Early Detection with Pervasive Computing

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Abstract. Embedded assessment leverages the capabilities of pervasive computing to advance early detection of health conditions. In this approach, technologies embedded in the home setting are used to establish personalized baselines against which later indices of health status can be compared. Our ethnographic and concept feedback studies suggest that adoption of such health technologies among end users will be increased if monitoring is woven into preventive and compensatory health applications, such that the integrated system provides value beyond assessment. We review health technology advances in the three areas of monitoring, compensation, and prevention. We then define embedded assessment in terms of these three components. The validation of pervasive computing systems for early detection involves unique challenges due to conflicts between the exploratory nature of these systems and the validation criteria of medical research audiences. We discuss an approach for demonstrating value that incorporates ethnographic observation and new ubiquitous computing tools for behavioral observation in naturalistic settings such as the home.

1 Introduction

Baby boomers, the cohort of adults born between 1946 and 1964, will contribute to a growing medical crisis in many industrial countries. As demographics shift and lifespans increase, a larger percentage of adults will require medical care. The rising cost of medical procedures in combination with the greater numbers of people needing assistance will place an enormous strain on healthcare providers. Many diseases that severely limit quality of life are difficult to manage in their later stages, but can be treated more effectively and less expensively if caught early. Early detection, therefore, is increasingly of interest to all parties in the medical system: individuals managing their health, family and medical caregivers, and medical researchers in search of predictive biomarkers.

This paper argues for a new approach to early detection that tightly integrates traditionally separate areas of monitoring, compensation, and prevention (Figure 1). Leveraging synergies in these three areas holds promise for advancing detection of

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disease states. We believe this highly integrated approach will greatly increase adoption of home health technologies among end users and ease the transition of embedded health assessment prototypes from computing laboratories into medical research and practice.

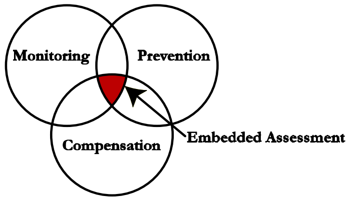

Fig. 1. Health technologies for early detection typically focus on monitoring, compensation, or prevention. We argue that the most powerful interventions may leverage all three areas simultaneously

We derive our observations from a series of exploratory and qualitative studies on ubiquitous computing for health and wellbeing. These studies, outlined in Table 1, highlighted barriers to early detection in the clinical setting, concerns about home assessment technologies among end users, and values of target user groups related to prevention and detection. Observations from the studies are used to identify challenges that must be overcome by pervasive computing developers if ubiquitous computing systems are to gain wide acceptance for early detection of health conditions.

Table 1. The research direction proposed in this paper is based on evidence from ethnographic studies on health needs and a series of concept feedback studies

Study Type	**Number of interviews**
Ethnographic needs assessment: Household interviews and shadows with older adults and their family members [1]	Full household interviews (44)
Concept feedback studies: Interviews using concept sketches and "informances" (live enactments of proactive health computing capabilities). See [2] for overview of methods.	Boomers (28), healthy elders (35), elders with Mild Cognitive Impairment (12)
Expert interviews: Discussion with researchers and clinicians about early detection, prevention, longitudinal monitoring and EA concepts	13 experts (neurologists, neuropsychologists, nurses, gerontologists)
Participatory design: Interviews using mocked-up data displays and longitudinal monitoring scenarios to elicit feedback about personal health tracking	26 Boomers, 5 elders, 8 professional caregivers (general practitioners, social workers)

2 Barriers to Early Detection

The motivation driving research on pervasive home monitoring is that clinical diagnostic practices frequently fail to detect health problems in their early stages. Often, clinical testing is first conducted after the onset of a health problem when there is no data about an individual's previous level of functioning. Subsequent clinical assessments are conducted periodically, often with no data other than self-report about functioning in between clinical visits. Self-report data on mundane or repetitive health-related behaviors has been repeatedly demonstrated as unreliable [3]. Clinical diagnostics are also limited in ecological validity, not accounting for functioning in the home and other daily environments. Another barrier to early detection is that age-based norms used to detect impairment may fail to capture significant decline among people whose premorbid functioning was far above average. Cultural differences have also been repeatedly shown to influence performance on standardized tests (e.g.,[4]). Although early detection can cut costs in the long term, most practitioners are more accustomed to dealing with severe, late stage health issues than subclinical patterns that may or may not be markers for more serious problems. In our participatory design interviews, clinicians voiced concerns about false positives causing unwarranted patient concerns and additional demands on their time.

Compounding the clinical barriers to early detection listed above are psychological and behavioral patterns among individuals contending with the possibility of illness. Our interviews highlighted denial, perceptual biases regarding variability of health states, over-confidence in recall and insight, preference for preventive and compensatory directives over pure assessment results, and a disinclination towards time consuming self-monitoring as barriers to early detection. Our ethnographic studies of households coping with cognitive decline revealed a tension between a desire for forecasting of what illness might lie ahead and a counter current of denial (see Figure 2) [1]. Almost all caregivers and patients wished that they had received an earlier diagnosis to guide treatment and lifestyle choices, but they also acknowledged that they had overlooked blatant warning signs until the occurrence of a catastrophic incident (e.g. a car accident). This lag between awareness and actual decline caused them to miss out on the critical window for initiation of treatments and planning that could have had a major impact on independence and quality of life. Ethnography and concept feedback participants attributed this denial in part to a fear of being diagnosed with a disease for which there is no cure. They also worried about the effect of this data on insurers and other outside parties. Participants in the three cohorts included in our studies (boomers, healthy older adults, and older adults coping with illness themselves or in a spouse) were much more interested in, and less conflicted about, preventive and compensatory directives than pure assessment.

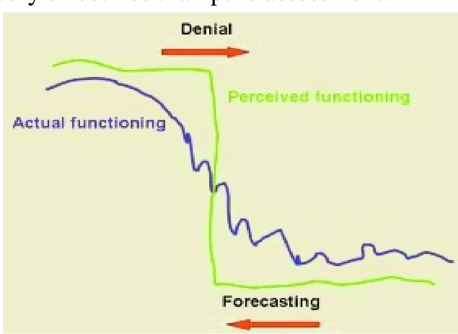

Fig. 2. This heuristic model, published in [1], extends a previous model by Hirsch et al. [5] to illustrate the perceptual and emotional factors that delay assessment

Perceptual biases also appear to impede traditional assessment and self-monitoring. Ethnography participants reported consistently overestimating functioning before a catastrophic event and appeared, during the interview, to consistently underestimate functioning following detection of cognitive impairment [1]. Additionally, we observed probable over-confidence among healthy adults in their ability to recall behaviors and analyze their relationship to both environmental factors and wellbeing. This confidence in recall and insight seemed exaggerated given findings that recall of frequent events is generally poor [3].

As a result of these health perceptions, many of those interviewed felt that the time and discipline required for journaling (e.g. of eating, sleeping, mood, etc.) outweighed the benefits. Additionally, they expressed wariness of confronting or being reprimanded about what is already obvious to them. They would prefer to lead investigations and develop strategies for improving their lives. Interviewees, particularly those in the baby boomer cohort, expressed a desire for highly contextualized analyses of health, posing questions such as "Is quality of time with my kids affected by my deadlines at work?" "Has my posture improved since I started doing yoga two months ago?" "At what time of day do I write the best and how can I schedule my time accordingly?").

Pervasive computing systems may enable this type of integrated, contextualized inquiry if they can also overcome the clinical and individual barriers that might otherwise impede adoption of the new technologies. Table 2 summarizes the *clinical* and *individual* barriers to health assessment and corresponding opportunities afforded by ubiquitous computing technologies that we identified from our interviews.

Table 2. Barriers to early detection and the corresponding ubicomp opportunities

***Clinical* Barriers to early detection**	**Opportunities afforded by ubiquitous computing technologies**
1. Delayed assessment: Patients and physicians typically do not request assessment until a problem arises and reaches considerable severity (e.g., it is often not until a car accident or fall that a patient's family requests cognitive assessment).	Continuously monitor and use data to encourage patients to seek help.
2. Infrequent assessment: Clinicians lack information about functioning and related behaviors between visits (e.g., cognitive tests are typically administered at most bi-annually, but the significant fluctuation in cognitive functioning -- over the course of a day, week and month -- could inform diagnosis).	Continuously monitor to illuminate patterns and daily variability; provide data directly to patients, who can present patterns to clinicians if they wish.
3. Lack of ecological validity: Clinicians typically lack reliable information about patients' functioning in environments of daily life (e.g., cognitive tests administered in the clinician's office may not reflect functioning in the home, car, or workplace).	Acquire contextually sensitive data to highlight environment-behavior connections and specific incidents that may not be reported in clinical visits.
4. Narrow focus of assessment: Patients and clinicians may overlook early symptoms that are not obviously tied the variable of direct interest (e.g., discoordination, in the case of dementia).	Use implicit sensing to detect subtle changes in manipulation of everyday objects.

5. Avoidance of testing for early detection: Some clinicians limit testing because of time, expense, and poor predictive value (e.g., genetic testing for Alzheimer's biomarkers is sometimes discouraged).	Direct embedded assessment services primarily to end users – *any* individuals interested in monitoring their own health, not only "patients."
***Individual* Barriers to early detection**	**Opportunities afforded by ubiquitous computing technologies**
6. Fear of diagnostic labels: Patients fear diagnosis of illnesses that have no known cure (e.g., Many dread a diagnosis of Alzheimer's disease because there is currently no curative treatment). Patients can also be frustrated by diagnoses that do not explain etiology of symptoms.	Frame feedback in actionable directives for compensatory and preventive health strategies.
7. Avoidance of testing experiences in clinical settings: Clinical assessment can be tiring, intimidating and seem futile. (e.g., Cognitive test batteries are sometimes experienced as a very long "pop quiz" that does not relate to the challenges of everyday life).	Embed assessment into services that have other value propositions. Assessment is woven into everyday routines and devices, assistive services, and mentally stimulating games.
8. Underestimation of health variability and overestimation of insight: Individuals' retrospective accounts and understanding of their own behavior are limited. (e.g., Past research shows that people significantly underestimate food consumption. [6])	Use feedback to highlight variability in health states and point out opportunities to leverage and extend positive health states.
9. Lack of time and discipline required for journaling behaviors and symptoms. (e.g., Patients' compliance with health behavior journals, such as those for tracking diet, tends to drop off quickly).	Automate and embed data capture into everyday activities; request and deliver information at system-detected opportune moments; ensure technology continuously reinforces its value.
10. Discordance between individuals' holistic, integrated view of health and the constraints of most self-monitoring systems. (e.g., Blood pressure cuffs and logs do not reflect the behavioral and environmental factors that influence readings)	Allow people to explore correlations between contextual and behavioral factors.
11. Privacy concerns: Fears about availability of diagnostic information to outside parties. (e.g., Many worry that, if shared, early signs of cancer or dementia may jeopardize medical coverage).	Direct feedback to end users not to caregivers, clinicians, or insurers.
12. Difficulty relating to traditional clinical health metrics and language (e.g., Criteria for mood disorders do not always resonate with individuals' experiences of stress and life dissatisfaction.)	Present tailored and interactive visualizations at appropriate moments related to personal routines.
13. "Proactive" focus on self-improvement, wellness and quality of life: Among Boomers and younger adults, healthful behavior is motivated largely by presentation and performance goals versus strictly defined health goals. Clinicians and current monitoring systems focus on existing problems and preventing high-risk illnesses.	Support users' current concerns, presenting trends of interest, even if these trends may not be directly relevant to clinical care (e.g., Boomers may be more likely to monitor their behavior if they can see its relationship to their immediate productivity and physical appearance versus their risk for cardiovascular disease). Track effectiveness of different cues (e.g., name prompts, posture adjustments from chairs) and feedback displays to inform assessment and self-directed wellness strategies.

3 Advances in Pervasive Computing for Health Management

New approaches to early detection are needed to overcome the significant barriers to health assessment outlined in Table 2. Developments in ubiquitous computing for health and wellbeing have largely been in three separate areas: Monitoring, compensation, and prevention.

3.1 Monitoring

Most prior work on the application of ubiquitous computing technology for healthcare has been in the area of monitoring. Ubiquitous computing researchers have advocated in-home and on-body monitoring to help people to assess their own health and that of their loved ones [7]. Numerous research efforts exist to develop systems that detect activities of daily living (e.g. [7-15]) and specific conditions, such as changes in gait [16]. Sensors embedded in the home are intended to collect longitudinal and contextually sensitive data that can then be processed to automatically detect important changes in behavior patterns caused by the onset of illness. Sensors on mobile devices for detecting patterns of activities have also been proposed [17]. These systems usually collect data continuously or when someone is engaged in a particular activity of interest, such as computer game playing [18].

The focus of much of the prior work on ubiquitous assessment is monitoring, rather than self-awareness – an emphasis that implies a receptive clinical audience. A few clinical trials are currently evaluating in-home monitoring systems (e.g. extensions of [15]), but it is not clear how these studies will address the expectations of medical audiences given their relatively small sample sizes and short (e.g. months) observation periods. Longitudinal, large number of subject studies correlating home and clinical assessment data are not yet feasible for most ubiquitous computing trials. Commercial systems are currently limited to a small number of sensors per dwelling, typically motion sensors, that do not track activities of particular interest, only variation from baseline movement throughout a home (e.g. QuietCare from Living Independently Group). Existing commercial systems provide no compensatory or preventive functionality using the sensors.

3.2 Compensation

Context-dependent information delivery has been explored by a number of researchers to compensate for health problems in later life. Several such systems, designed to help people compensate for cognitive and physical decline [19], are intended to promote independence in and outside the home [17]. Context-aware computer reminding systems have been developed to help people compensate for attentional deficits by reorienting them after they are interrupted from a sequential task such as cooking [19]. Other systems use ubiquitous computing to help people compensate for memory loss by prompting them to take medications [20, 21]. Ubiquitous computing systems have also been proposed to help people remain socially engaged by compensating for impaired recall of names and faces [22], providing visual feedback on social activity to elders and their caregivers [23], and forging connections between people with common interests in social settings [24].

The compensatory systems proposed by ubiquitous computing researchers have typically been demonstrated with prototypes. Few have been tested outside of a laboratory setting or with a plan for gaining acceptance by medical or lay communities.

3.3 Prevention

Context-dependent information delivery has prompted research on preventive health care innovation. "Just-in-time" information delivery systems have been conceptualized to encourage healthy behaviors that either lower the probability of serious illness of those at risk (primary prevention) or help prevent worsening of an illness (secondary prevention) by automatic detection of particular situations or activities [25]. Behavior change is motivated through the delivery of information at key times in the decision making process: points of decision, behavior, and consequence [26]. The promise is to create systems that would, like an effective personal trainer, provide tailored messages at teachable moments – the right place and time when a person is receptive to information – in order to motivate behavior, belief, or attitude change. Ubiquitous computing technologies that simplify data collection and provide summary information may lead to more informed decision making, for example using receipt analysis as a behavioral feedback tool to improve nutritional choices [27].

Many of the preventive technologies developed by medical researchers have been designed for people who are vulnerable to particular illnesses. For example, a number of websites and internet therapies have been tested with people at risk for obesity, diabetes or eating disorders (e.g., [28]). There have also been a number of primary prevention applications designed for the general population, such as desktop applications to help people track their health goals, kiosk-based systems for people to encourage better dietary decision making in supermarkets (e.g. [29]), and the more recent products, such as Sport Brain (SportBrain Holdings, Inc.), that allow people to monitor their exercise. It is our impression, from consumer trends and anecdotal evidence, that the most enthusiastically adopted and effective preventive health systems may be those that are primarily designed for fun rather than health management. For example, the increasingly popular "Dance Dance Revolution" (Konami Corporation), although designed strictly for entertainment, is rich in the social, cognitive and physical stimulation that may prevent diseases such as dementia [30]. Such consumer-oriented games may be especially valuable preventive tools for people who are not already experiencing a serious health issue. Research is needed on the health value of such games and how their capabilities can be extended to assess performance over time, and provide customized programs depending on individuals' agility and health concerns.

4 Embedding Assessment into Daily Life and Wellness Strategies: Integrating Monitoring, Compensation, and Prevention

Evidence from needs assessment and iterative concept feedback studies suggests that assessment will be most sensitive and most well used if it is embedded not only in the home environments but also into individuals' compensatory and preventive strategies.

4.1 Definition of Embedded Assessment

We define the following requirements for *embedded assessment* (EA)*:*

- EA applications should simultaneously serve three purposes: monitoring, prevention, and compensation.
- EA applications should use "extreme personalization" in the way that information is acquired and presented. Monitoring, prevention, and compensation are embedded in the user's everyday physical environments, behavioral repertoires and social milieus. Explicit assessment, which requires conscious engagement from users, occurs at times that make sense during natural activities, and it involves content that is relevant to the end user's life (work, social, family, etc.). Implicit or passive monitoring is integrated into the activities and tools of daily life (e.g., phones that trend changes in the way they are operated, mirrors that capture and reflect subtle changes in appearance).
- EA applications monitor health status by trending the degree and quality of assistance (in the form of hints, prompts, encouragement and adaptive system adjustments) required for particular activities. EA systems search for meaningful patterns that can inform self-directed wellness strategies or medical care.

Monitoring will typically be the least prominent aspect of the user experience in EA. Monitoring is the continuous and contextually sensitive capture of data (physiological, behavioral, or psychological) that are salient to the user and his or her goals. EA monitoring is designed for self-directed inquiry rather than observation by a third party. The data may be only loosely tied to health (e.g., self-presentation, appearance, interpersonal dynamics, posture, etc.) or may be more obviously health related (e.g., eating and sleeping patterns, skin changes, pain). Monitoring can be of normal day-to-day behaviors (e.g., looking for changes in how one operates a remote control, cell phone or VCR) or of performance on tasks that are deliberately undertaken for preventive or compensatory purposes. The data capture is intended for feedback that will allow the end user to explore environment-behavior relationships and develop self-initiated health management strategies.

Compensatory strategies supported in EA are the adjustments a user makes to cope with a health concern. A compensatory strategy can include encoding, rehearsal and organizational strategies to compensate for a memory loss, self-reflection and mindfulness to address negative mood states, medical treatments, dieting, cosmetic procedures, physical therapy, or the use of assistive technologies. EA technologies can be interwoven with these activities, or the technologies themselves can offer the compensatory support. For example, rehearsal exercises and prompts could be offered on a mobile computing device to compensate for memory loss, or the compensatory support could be provided in the form of a visual display of monitoring data intended to invite mindfulness about variability in performance and health. EA technologies can also adjust to help users accomplish a task, such as programming a VCR, or offer graduated prompts for preparing a cup of tea.

Preventive strategies supported in EA are activities that protect against a health concern. Preventive strategies may include cognitive and physical exercise, social engagement, and dietary changes. EA technologies can monitor these activities and provide motivating behavioral feedback. Alternatively, EA applications, such as mentally challenging games presented on a mobile phone, can provide both the interface for the preventive activity and the mirroring of performance trends on this activity.

One example EA application that combines monitoring, preventive activity, and compensatory strategies (that the authors are developing) is a game for families on mobile phone plans. The game is designed to provide *monitoring* by tracking the response times and error rates as family members use the application to send family quiz questions to one another. The quiz items will be structured so that they exercise aspects of memory and reasoning that are typically the focus of cognitive assessment. Trending on users' engagement in this shared activity might provide early indicators of cognitive decline. C*ompensatory strategies* will be supported as the feedback from the game helps individuals identify their strengths and weaknesses, along with the cuing and problem solving approaches that are most helpful for them. Additionally, the system will allow people to practice compensatory strategies such as rehearsal, encoding, mental manipulation of information, and drawing on the memory of family members. The game supports *prevention* of cognitive decline by engaging users with mentally stimulating quiz items, encouraging users to author questions and answers that ultimately generate a family knowledge archive, and by increasing social contact with their extended family.

5 Meeting the Demand for Evidence-Based Health Systems: Challenges of Evaluating Embedded Assessment Technologies

To help early detection of disease states, embedded assessment systems will ultimately need to appeal to both end users and medical audiences. Demonstrating value to these two groups will require empirical evidence of their concurrence with standardized measures, predictive power for early detection, and their effectiveness in guiding end users in self-governed health care initiatives. Similar validation challenges are shared by the many pervasive computing researchers who are developing innovative health care technologies (e.g. see [31]) and other applications for the home. The traditional methods for evaluating and validating assessment techniques within social sciences and medicine require longitudinal studies with very large sample sizes. Such studies would examine the concurrent validity of EA with other measures and, through retrospective analysis, the predictive power of EA as a biomarker for particular health conditions.

To establish concurrent validity, the accepted metric in clinical assessment research, individuals' performance on embedded assessment applications would be compared to their performance on standardized clinical measures over a longitudinal study. Participants would engage with embedded assessment tasks on a daily basis and complete standardized clinical tests or measurements at regular intervals. Attention would be paid to general agreement in the trends (e.g., whether steady decline is apparent in both forms of testing) and to agreement between specific measures (e.g., whether declines in ability to accurately dial telephone numbers parallel scores on standardized tests of working memory).

To examine the predictive power of EA prototypes, one might retrospectively compare the embedded assessment performance of people who had started using the prototypes when healthy but then differentially developed disease (e.g. comparing those who developed Alzheimer's Disease to those with normal cognitive aging). Patterns on EA performance that distinguished these two groups would be used to generate hypotheses about early markers. Needless to say, this approach is challenging. It typically requires matching participants on both baseline health status and end-point diagnosis, and tracing cognitive functioning and other health factors throughout the lifespan.

Home health technology is typically evaluated in a clinical setting and subsequently migrated to the home. Devices such as blood pressure monitors, for example, were extensively tested in hospitals and later adapted for home use. Similarly, defibrillators have recently been shifted into home usage after extensive clinical testing. EA technology, however, by its embedded nature, cannot be evaluated out of context. Furthermore, many EA technologies will require sensor infrastructures in homes that cannot be evaluated in a piecemeal fashion – the *entire* sensor infrastructure must be available to detect baseline health behaviors on embedded tasks. Evaluation of EA technology is made even more complex by the integration of monitoring, preventive activities, and compensatory strategies. The impact of each component may confound experimental studies looking at one outcome variable. Therefore, researchers interested in EA face a classic "chicken and egg" evaluation problem. To make a (statistically) convincing argument that EA systems can provide useful biomarkers of early onset of disease will require studies where EA technology is installed in many homes for long evaluation periods, most likely of months or years. To justify the cost of a sufficient number of installations, however, will require evidence of the preventive health value of the EA systems.

Our interviews suggest that demand from end users for EA technologies may be sufficient to jumpstart adoption. Preliminary evaluation of EA might therefore focus not on biomarker identification, but on the benefits and obstacles experienced by end users. This approach would use a separate set of ubiquitous computing tools to observe usage and effects of EA systems. Key issues are whether systems enable users to determine meaningful patterns in their health and behavior, and whether these patterns drive behavioral change and health improvement. Traditional usability approaches can be used to examine adoption. Iterative open-ended interview questions, structured exercises, and ethnographic observation can illuminate whether the EA systems were effective in influencing awareness of variability in behavior and in mental and physical health. Demonstration of value to end users from compelling pilot studies may ultimately lead to wide-scale adoption of EA technologies. At that time, large-n trials may be undertaken to evaluate long-term effects; results of such trials could reveal bio and behavioral markers from embedded sensing.

Evaluation of the end-user's experience with EA systems should also incorporate observational tools such as live-in labs [32] and in-home sensors [33]. These tools, increasingly employed to evaluate other types of ubiquitous computing technologies, would generate detailed descriptions of EA usage. Users' everyday experience with EA systems will be important to assess, but difficult to gather through retrospective report. Prototype EA systems deployed in live-in labs and a limited number of homes could detect change in some metrics of adoption: usage, elaboration of features and content, sharing, interaction with systems and other people using the systems in the context daily routines. These adoption measures could be examined to make sense of test performance. In highly instrumented environments, the same sensors used to deploy EA prototypes could be used to provide contextual information related to metrics of adoption, such as physical activity levels, time spent in different activities and areas of the home, and interaction among members of a household or social network.

Time-based evaluations, conducted in an instrumented residential lab or home setting, may also provide compelling evidence of value of an EA prototype. Pervasive computing monitoring is intrinsically well suited to demonstrate variability across time and place. Such analyses may illuminate compelling patterns in behavior, cognitive functioning and other aspects of health. Our Boomer interviewees suggested they might be interested in tracking such variability when managing their own health. Any measured variability might also be of interest to medical researchers interested in early markers or outcome assessment and clinicians trying to hone their diagnoses. Based on these observations, pilot studies that can convincingly demonstrate variability that can be partially explained by context or daily routine variables, such as sleep patterns or time of day, are recommended. Such studies might suggest to researchers that they are missing valuable information when only examining health changes over long intervals and may lead the way to funding for larger scale EA studies in real homes. Until EA systems are widely deployed, researchers will lack evidence on which of the many potential embedded measures provides useful, contextual health markers. Tools are needed, therefore, with a battery of potentially valuable sensors ubiquitously installed to provide data for exploratory identification of the most promising marker strategies.

6 Conclusion

The embedded assessment approach emerged from the series of needs gathering and concept feedback studies and interviews involving a total of 171 people, as listed in Table 1. The general approach of embedded assessment arose as a means of resolving conflicting attitudes about early detection. Our early studies indicated that to be tolerable to end users, assessment needed to be embedded not only with the environments of daily living, but also within accepted compensatory and preventive health strategies. For many types of health assessment, such as cognitive assessment, baselines of functioning must be established during middle age. Many useful proactive health applications, therefore, will need to be relevant and stimulating to this cohort. Our work suggests a promising approach for future research would be to embed health assessment within the social unit of the family, in part because interpersonal connectedness is so highly valued to people at all stages of life. A promising approach may be to focus on developing prototype systems for individuals in midlife who are managing their own health. Other potential users, including family and medical care providers and researchers searching for new biomarkers of disease, will most likely respond to interest from these first two groups rather than initiate usage.

We believe individuals in mid life are the most likely adopters of embedded assessment technologies. Nonetheless, researchers must carefully consider the needs and validation metrics of both groups: the boomer's desire for constructive, insightful and motivating feedback on health, appearance, performance, and the medical researcher's desire for identified biomarkers with predictive power for disease progression. Traditional methods of demonstrating test validity and predictive power of embedded assessment for medical audiences are not immediately feasible for pervasive computing trials. In the absence of such metrics, we argue for outcome measures that will demonstrate the effectiveness of embedded assessment systems as health interventions and self-reflective tools. Demonstration of variability in functioning as a function of context (temporal, environmental, behavioral and social) would be compelling to both end consumers and medical communities. To demonstrate this variability and other metrics of interest to target users, we suggest a tiered validation approach that involves in-home trials and focused observations in live-in laboratories. We believe this approach and our more general discussion of evaluation challenges can guide evaluation of the many innovative prototypes generated by the pervasive computing community for health assessment.

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References

1. Morris, M., et al., *New perspectives on ubiquitous computing from ethnographic studies on cognitive decline*, in *Proceedings of UbiComp 2003: Ubiquitous Computing*, J.F. McCarthy, Editor. 2003, Springer: Berlin Heidelberg. p. 227-242.
2. Lundell, J. and M. Morris, *Tales, tours, tools, and troupes: A tiered research method to inform ubiquitous designs for the elderly*, in *People and Computers XVIII - Design for Life*, Fincher, et al., Editors. 2004, Springer Verlag: London. p. 165-177.
3. Gorin, A.A. and A.A. Stone, *Recall biases and cognitive errors in retrospective self reports: A call for momentary assessments*, in *Handbook of Health Psychology*, A. Baum, T. Revenson, and J. Singer, Editors. 2001, Erlbaum: Mahwah, NJ. p. 405-413.
4. Kennepohl, S., et al., *African American acculturation and neuropsychological test performance following traumatic brain injury.* Journal of the International Neuropsychological Society, 2004. **10**: p. 566-577.
5. Hirsch, T., et al., *The ELDer Project: social, emotional, and environmental factors in the design of eldercare technologies*, in *Proceedings of the Conference on Universal Usability.* 2000.
6. Bingham, S., *The dietary assessment of individuals: methods, accuracy, new techniques and recommendations.* Nutr Abstr Rev, 1987. **57**: p. 705-42.
7. Mynatt, E.D., I. Essa, and W. Rogers, *Increasing the opportunities for aging in place*, in *Proceedings of the Conference on Universal Usability*. 2000. p. 65-71.

8. Munguia Tapia, E., S.S. Intille, and K. Larson, *Activity recognition in the home setting using simple and ubiquitous sensors*, in *Proceedings of PERVASIVE 2004*, A. Ferscha and F. Mattern, Editors. 2004, Springer-Verlag: Berlin Heidelberg. p. 158-175.
9. Philipose, M., et al., *Guide: Towards understanding daily life via auto-identification and statistical analysis*, in *Ubihealth 2003: The 2nd International Workshop on Ubiquitous Computing for Pervasive Healthcare Applications*. 2003.
10. Wilson, D. and C. Atkeson, *Automatic health monitoring using anonymous, binary sensors*, in *CHI Workshop on Keeping Elders Connected*. 2004.
11. Matsouoka, K., *Smart house understanding human behaviors: Who did what, where, and when.* Proceedings of the 8th World Multi-Conference on Systems, Cybernetics, and Informatics, 2004. **3**: p. 181-185.
12. Haigh, K.Z., et al., *The Independent LifeStyle AssistantTM (I.L.S.A.): Lessons Learned*. 2003, Honeywell Laboratories: Minneapolis, MN.
13. Korhonen, I., P. Paavilainen, and A. Särelä, *Application of ubiquitous computing technologies for support of independent living of the elderly in real life settings*, in *UbiHealth 2003: The 2nd International Workshop on Ubiquitous Computing for Pervasive Healthcare Applications*. 2003.
14. Mihailidis, A., et al., *An intelligent environment to support aging-in-place, safety, and independence of older adults with dementia*, in *UbiHealth 2003: The 2nd International Workshop on Ubiquitous Computing for Pervasive Healthcare Applications*. 2003.
15. Barger, T., D. Brown, and M. Alwan, *Health status monitoring through analysis of behavioral patterns*, in *Proceedings of the 8th Congress of the Italian Association for Artificial Intelligence (AI*IA) on Ambient Intelligence*. 2003, Springer-Verlag.
16. Dockstader, S.L., M.J. Berg, and A.M. Tekalp, *Stochastic kinematic modeling and feature extraction for gait analysis.* IEEE Transactions on Image Processing, 2003. **12**(8): p. 962-976.
17. Patterson, D.J., et al., *Inferring high-level behavior from low-level sensors*, in *Proceedings of UBICOMP 2003*. 2003, Springer-Verlag.
18. Jimison, H.B., et al., *Home monitoring of computer interactions for the early detection of cognitive decline*, in *Proceedings of the IEEE Engineering in Medicine and Biology Conference*. 2004.
19. Mynatt, B.D. and W.A. Rogers, *Developing technology to support the functional independence of older adults.* Aging International, 2002. **27**(1): p. 24-41.
20. Pollack, M.E., et al., *Autominder: an intelligent cognitive orthotic system for people with memory impairment.* Robotics and Autonomous Systems, 2003. **44**(3-4): p. 273-282.
21. Floerkemeier, C. and F. Siegemund, *Improving the effectiveness of medical treatment with pervasive computing technologies*, in *UbiHealth 2003: The 2nd International Workshop on Ubiquitous Computing for Pervasive Healthcare Applications*. 2003.
22. 22. Morris, M., J. Lundell, and E. Dishman, *Ubiquitous computing for Mild Cognitive Impairment: A prototype for embedded assessment and rehearsal*, in *The Gerontologist*. 2003. p. 403.
23. Morris, M., J. Lundell, and E. Dishman, *Computing for social connectedness*, in *Proceedings of CHI 2004*. 2003.
24. nTag Interactive, *nTAG*. 2004.
25. Intille, S.S., *A new research challenge: persuasive technology to motivate healthy aging.* Transactions on Information Technology in Biomedicine, 2004. **8**(3): p. 235-237.
26. Fogg, B.J., *Persuasive technologies.* Communications of the ACM, 1999. **42**(5): p. 27-29.

27. Mankoff, J., et al., *Using low-cost sensing to support nutritional awareness*, in *Proceedings of Ubicomp 2002*, G. Borriello and L.E. Holmquist, Editors. 2002, Springer-Verlag. p. 371-378.
28. Winzelberg, A.J., et al., *Effectiveness of an Internet-based program for reducing risk factors for eating disorders.* Journal of Consulting and Clinical Psychology, 2000. **68**: p. 125-138.
29. Anderson, E.S., et al., *A computerized social cognitive intervention for nutrition behavior: Direct and mediated effects on fat, fiber, fruits, and vegetables, self-efficacy, and outcome expectations among food shoppers.* Annals of Behavioral Medicine, 2001. **23**(2): p. 88-100.
30. Fratiglioni, L., P.-B. S., and B. Winblad, *An active and socially integrated lifestyle in late life might protect against dementia.* Lancet, 2004. **3**: p. 343-353.
31. *UbiHealth 2003: The 2nd International Workshop on Ubiquitous Computing for Pervasive helthcare Applications*. 2003.
32. Intille, S.S., et al., *A living laboratory for the design and evaluation of ubiquitous computing interfaces*, in *Extended Abstracts of the 2005 Conference on Human Factors in Computing Systems*. 2005, ACM Press: New York, NY.
33. Intille, S.S., et al., *Tools for studying behavior and technology in natural settings*, in *Proceedings of UbiComp 2003: Ubiquitous Computing*. 2003, Springer: Berlin Heidelberg. p. 157-174.