Towards Ability-Based Optimization for Aging Users

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ABSTRACT
This paper addresses the design of user interfaces for aging adults. Older people differ vastly in how aging affects their perceptual, motor, and cognitive abilities. When it comes to interface design for aging users, the "one design for all" approach fails. We present first results from attempts to extend ability-based design to the aging population. We describe a novel approach using age-related differences as the principle of optimizing interactive tasks. We argue that, to be successful, predictive models must take into account how users *adapt* their behavioral strategies as a function of their abilities. When combined with design optimization, such models allow us to investigate optimal designs more broadly, examining trade-offs among several design factors. We present first results on optimizing text entry methods for user groups with different age-related declines.

Author Keywords
Ability-based design; model-based UI optimization; touch-WLM; aging population; motor performance

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION
By the year 2050, aging populations are expected to cover 27% and 15% of developed and developing nations, respectively [9, 11]. This paper is motivated by the need to design user interfaces (UIs) that better take into account age-related changes in physiological (e.g., sensation, tremor), perceptual (e.g., visual acuity, oculomotor performance), and cognitive abilities (e.g., task-switching). We address the fact that consequences of aging can be very diverse. Every user is different. As people grow older, the ability to regulate finger posture decreases [34], as does visual acuity [20]. Cognitive abilities as learning, memory retrieval, and attention are impacted negatively [6, 21]. Importantly, while age is clearly associated with decreases in abilities, a person's nominal age is not the determining factor. Some individuals are completely healthy at age 90, and others frail at 60 [5]. There is plenty of between-individual variance in sensorimotor and cognitive capabilities even within persons of the same age.

Individual differences are important to address in the design of more efficient and enjoyable technology for aging adults, just as they are for the mass market. Current smartphone interfaces tend to follow a "one design for all" approach. For example, the $DORO^{TM}$ smartphone (Figure 1), targeted specifically for older adults, offers the regular Android virtual keyboard for text entry. However, aging users have issues with smaller target and finding keys. In other parts of the UI, like the menu, elements are made overly large and colorful. Is this the best UI for somebody with, say, issues with tremor but with perfect vision?

The main goal of this work is to better address *individual differences* brought about by aging. To this end, we build on Wobbrock et al.'s [37] *ability-based design*, which has previously targeted users with disabilities. Our goal is to formu-

Figure 1. User interfaces for older adults often trivialize their cababilities, either dropping functionalities or making elements overly large and salient, stigmatizing the user. This paper presents results from a computational approach to customizing UI designs better to individual capabilities (here: $DORO^{TM}$ Liberto 820).

ITAP '16, October 20-22, 2016, Kochi, Japan.
© 2016 ACM ISBN 978-1-4503-4746-4/16/10...$15.00.
DOI: http://dx.doi.org/10.1145/2996267.2996275

late individual differences parametrically in a model that can produce realistic task performance with a given UI, and use this model to drive design optimization. We argue that predictive models must take into account not only differences in abilities but how users adapt their behavioral strategies as a function of their abilities. When combined with design optimization, such models allow us to investigate optimal designs more broadly, examining trade-offs among several design factors. We present first results from model-based exploration of the design of text entry methods for user groups with different effects of aging. We show our keyboard layouts covering different cognitive, perceptual and motor effects namely, essential hand tremor or Parkinson's, less visual search ability and disability in reading.

RELATED WORK

Our work is positioned in the field of ability-based design, but utilizing optimization methods to construct designs, and targeting individual differences in capabilities due to aging.

Model-based UI optimization

Stuart Card and colleagues proposed the first full-fledged simulation of a user, GOMS, for HCI, in 1983. Instead of guesswork or expensive studies, a designer would evaluate an interface by simulating how users perceive, think, and act when completing tasks. Subsequent models (e.g., ACT-R) predicted not only task completion time but errors and memory load. To aid practitioners, mathematical simplifications (KLM and GLEAN) and interactive modeling environments were developed (CogTool), yet these were not combined with algorithms that could *generate* designs.

HCI research using combinatorial optimization methods—such as simulated annealing—to generate design started in early 2000 to explore the use of realistic human performance. During the last 16 years, this work has been extended to menus [3], layouts [35], and gestures [33] among others. Model-based UI optimization uses combinatorial optimization and predictive models of human behavior in objective functions of these algorithms. Design problems are defined as search for an optimal design in a set of candidate designs. The main benefit of the approach over heuristic and machine learning methods is that a design can be produced for meaningful and well-defined objectives, such as usability or learning. These methods do not stop at searching for a single "best" design; they explore the space for surprising alternatives too. Critically, design follows from first principles, and those principles are scrutinizable and can be questioned. Model-based UI optimization might offer a flexible and powerful toolbox for ability-based design. However, with the exception of SUPPLE (see below), model-based UI optimization has not been targeting individual differences. Our work looks at differences brought about by aging, in particular.

Ability-based design

Recent papers have explored methods for capturing, measuring, and modeling the abilities of diverse users [8, 13, 14, 22, 23, 25, 27, 28]. Large variations in human abilities yields hard challenges to sensing, inference, abstraction, and measurement. However, according to Gajos et al. [14], ability-based interfaces can be developed if this problem can be solved.

Although ability-based design can be achieved without automatic adaptation, recent advances in adaptive UIs are promising. Achievements in automatic personalized UI generation [12], ephemeral adaptation [10], adaptation to user skills [22], and adaptation to changing contexts [24] demonstrate that interactive technologies can detect and adapt to a users abilities, and therefore support an ability-based design approach.

Prior works in ability-based design has been mainly focused on designing specialized hardware which can help the disabled to access the non-adapted software [37]. These approaches may improve the cost-efficiency, simplicity, as well as lower configuration and maintenance costs, as well as decrease the abandonment rate of such specialized systems [4, 17, 26]. Some older adults (mainly above 80 years of age) have problems to use touchscreen devices, at times due to being unaware of the interaction style.

Gajos et al. [12] introduced *SUPPLE* framework which is similar to the one presented here. However, it uses decision-theoretic optimization to automatically generate UIs adapted to a person's abilities, taking also into account devices, preferences, and tasks. However, some of these are implemented heuristically, making it hard to resolve conflicts due to contradictory objectives (e.g., make buttons bigger at the same time as making use more efficient overall). Our goal is to select a design through parametric optimization technique that models each user's individual abilities and predicts how they contribute to their overall task performance. This allows for optimizing for a single objective (e.g., task completion time) without heuristics. We also contribute by addressing a domain (text entry on touchscreens) not addressed before.

Individual differences and aging

The most striking factor about age-related change is its variability. It is to be noted that the cognitive decline is not inevitable. Some elderly maintain excellent cognitive function into their 70s and 80s and perform similar or better than younger counterparts. Others show signs of decline by the age of 60. In addition, it is observed that decline is not uniform across capabilities. As an example, some older adults have excellent executive functions (cognitive control and supervisory attentional system) but impaired episodic memory function, and vice versa [16]. What accounts for this variability is of considerable interest to researchers and to the increasing numbers of older people who want to ensure that their cognitive functioning remains intact well into their later years.

Inter-individual variability is an important aspect to be considered while developing biological, psychological, and health-related applications. Agarwal and Prasad [1] stated individual differences as an important aspect to be considered toward developing information technology applications. For example, recent functional neuroimaging studies have observed different patterns of brain activation in older and

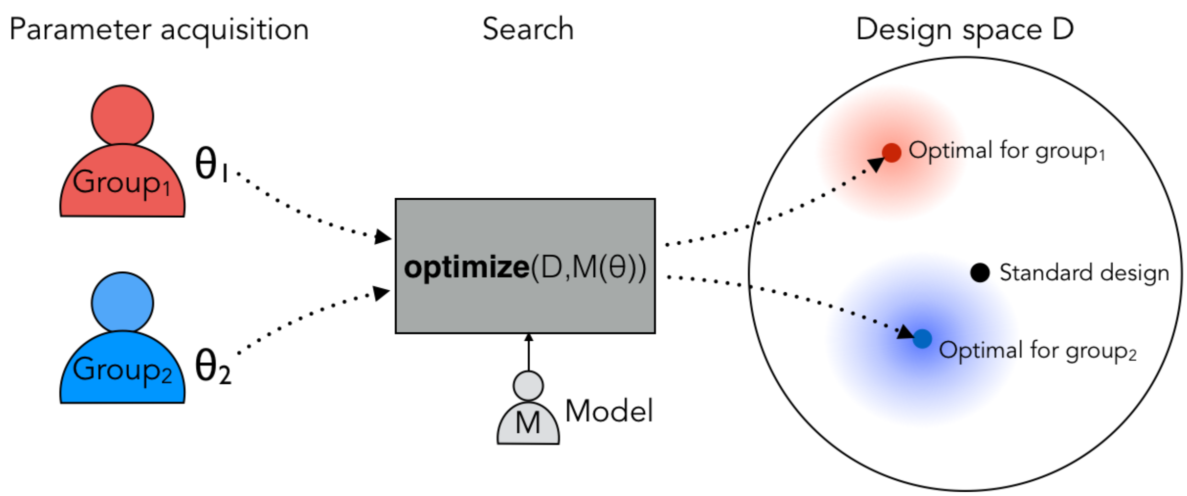


Figure 2. Overview of parametric optimization of user interfaces in ability-based design. User groups are described as sets of model parameters (θ). The parametrized model $M(\theta)$ is used in an optimizer to search for customized designs. The model used in the case presented here assumes that users adapt optimally to a design after experience (rational analysis).

younger adults while performing identical memory or working memory tasks [18, 29]. Such brain activation changes relate to declining sensory and perceptual abilities [31], which older people compensate for in a variety of different ways.

Age-related changes in cognition are not uniform across all cognitive domains nor across the aging populations. Attention and memory are the two basic cognitive functions most affected by age [32, 11]. Evidence suggest that some aspects of attention and memory hold up well with age while others show significant decline. Age also affects higher-level cognitive functions such as language processing and decision making [15]. Moreover, a set of executive functions manage and control various component of the complex cognitive tasks. Many studies observed that the impairment of such executive functions becomes a key factor for age-related declines.

Researchers have recently started to build models with parameters predicting age-related changes. Trewin et al. [36] showed that whereas a pointing performance model for younger adults fits with real data well, it fails to predict individual differences in pointing performance. Therefore, it becomes a challenge to select parameters for building models supporting older adult performance, by considering individual variations.

Summary
Although ability-based design has been found effective for disabled users and has potential to extend toward addressing problems of older adults, it faces problems as the variation in older people's abilities is very high. For example, there exists large variability in visually search strategies in the smartphones among young old, middle old and old old persons. It is, therefore, easier to design effective interfaces satisfying a specific ability, but very hard to come up with an optimal design solution, supporting adaptability over all variations in abilities. We propose ability-based optimization approach, which computationally selects the optimal design from large design space based on design and cognitive task model parameters tuned for elderly users

APPROACH
This paper extends model-based UI optimization to ability-based design. Figure 2 provides an overview of the approach. A UI optimization task, in general, consists of a finite set of candidate designs, an objective function, and constraints. Hence, application to ability-based design critically rests on formulation of objective functions in such a way that individual differences can be expressed as part of the objective function. We here explore the idea to express individual differences as parameters (θ) of a predictive model. We call this the parametric approach.

This work extends ability-based optimization from the consideration of motor performance difference. As discussed above, first implementations of this idea were shown by Gajos and colleagues (e.g., [14]). However, they were limited to models of motor performance combined with simple heuristics to describe visual impairments. The problem with heuristics (such as "users with poor vision need a larger font") is that they are not able to resolve trade-offs in design. Lacking a common unit of analysis, such as task completion time in our case, it is not possible to say how much one design factor can be changed without overly compromising another. If a single task-level model can handle all such factors, we can collapse the optimization task to a single objective.

Another advance examined here is the use of *rational analysis* to predict how a user with given characteristic might start using a UI. We assume that interaction with a UI is associated with a space of possible strategies. One well-known strategy is speed–accuracy trade off in pointing: a person's decision to be faster at the expense of accuracy, or vice versa, be more accurate but at the expense of speed. The identification of relevant strategy spaces is outside this paper.

Procedurally, parametric model-based UI optimization has the following steps:

1. Task definition: Defining design space D and objective function
2. Model construction: Constructing a parametrizable predictive model M of user behavior, including strategy adaptation
3. Parameter acquisition: Acquiring parameters θ to describe abilities of a user group
4. Optimization: Constructing an efficient combinatorial approach to solve the task
5. Assessment: Testing the robustness of the design to differing assumptions (e.g., change in parameters or task)

In the following, we describe out attempts to address these issues. We have worked on the problem of typing on smartphone devices, and the individualization of designs with regard to personal abilities that change due to aging. We develop a multi-parameter model of typing and explore the consequences various assumptions on what would be the most suitable design groups with differing abilities.

CASE: TEXT ENTRY ON TOUCHSCREEN DEVICES

Our goal is to improve the text entry methods on smartphone devices for aging users. Figure 3 depicts the predominant text entry UI. The figure also shows four design factors which we consider here, namely 1) number of rows in the word prediction list (WPL), 2) row height, 3) number of words to be provided in each row of the list, and 4) number of rows in text display area.

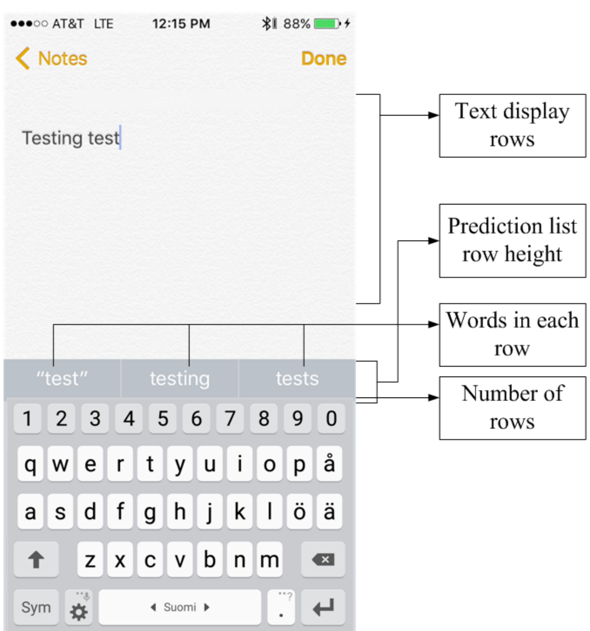


Figure 3. We explore the optimization of smartphone UIs to user groups with different characteristics. In this case, we optimize four design factors in touchscreen-based text entry.

We selected this case for its potential gains for older users. For example, for older users with tremor problems (e.g., essential tremor or Parkinson's), it would be better to make the key size bigger. However, this can only be done by grouping more than one letter onto a single key. While grouping may sound like a promising solution, it makes entry ambiguous, requiring an algorithm to disambiguate intended words. One could also increase the number of choices offered in the word prediction list (WPL). However, this introduces additional search time, which may be a problem in particular for users with poor visual acuity. Considerations like these show that the ”one design fits all” is ineffective for older adults.

Design Space

We describe the design parameters with their value ranges:

1. Number of rows in the prediction list: Usually, all the android and iOS keyboards have single row for the prediction list. We accommodate a range of 1–5 rows for the prediction list.
2. Elements in each row of the prediction list: Most of the Android and iOS keyboards contain 3 words in a row, but some still adjust based on the length of the predicted words (in that case, maximum 5 words). In the following analyses, we have fixed this number as 3.
3. Row height: The usual row height of the existing popular Android and iOS layouts is the same as the character key height. In the following, we vary the height in the range of 0.03%–0.07% of the height of the screen.
4. Number of rows in text display area: Almost all Android and iOS keyboard designs reserve most of the screen area for text display. We vary the number of rows between 2 and 7, whereas each row height is of the same as the key height.

In this work, apart from the baseline QWERTY layout (Figure 3), we consider grouped layout as another alternative input for the model and the optimizer. It minimizes the errors caused due to ‘fat finger’ problem as well as ensures fewer error in tapping for users having finger tremor or Parkinson's. We select three types of group: 3×3, 5×2 and 10×1. We design these baseline and grouped keyboard layouts for the design space in both English and Finnish languages. Two Finnish group keyboard layouts are shown as Figure 4a and 4b.

TOUCH-WLM

Touch-WLM is a predictive model for individual differences in text entry with smartphone devices using touchscreens. *Touch-WLM* is a word-level model (WLM) of text entry. While at the lowest level, it consists of deterministically executed (”keystroke-level”) sensorimotor actions, it also includes strategic decisions taken place at a higher level of control occurring at word-level. An overview of the model is given in Figure 5. It is used in the subsequent optimizations as the objective function. Importantly, it can be parametrized to describe the characteristics of a particular user group. Moreover, it includes a mechanism to find optimal strategy in small strategy spaces (rational analysis).

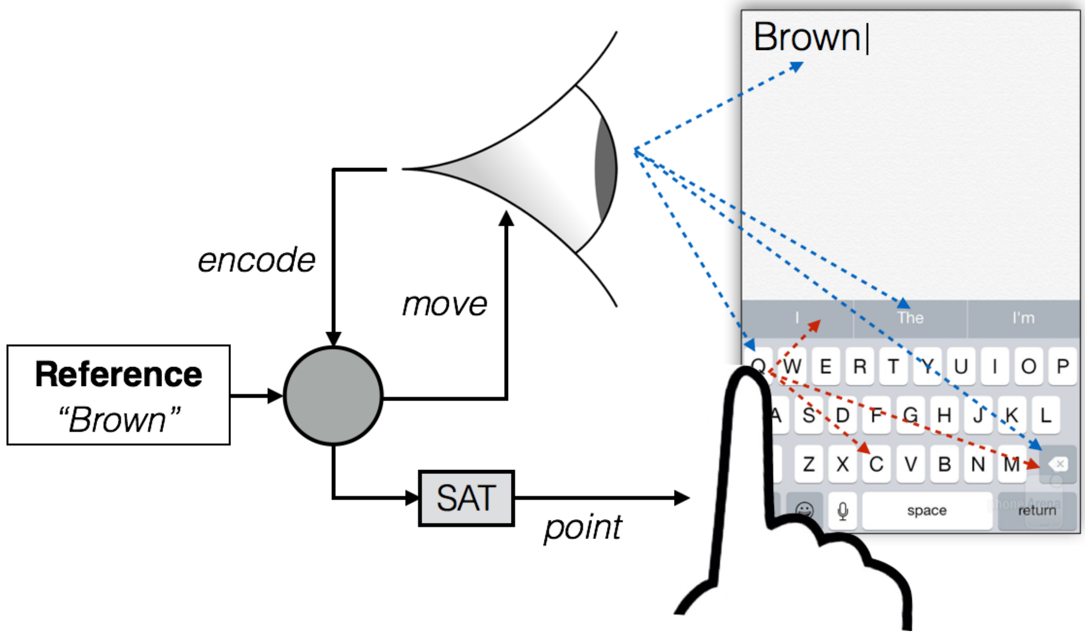
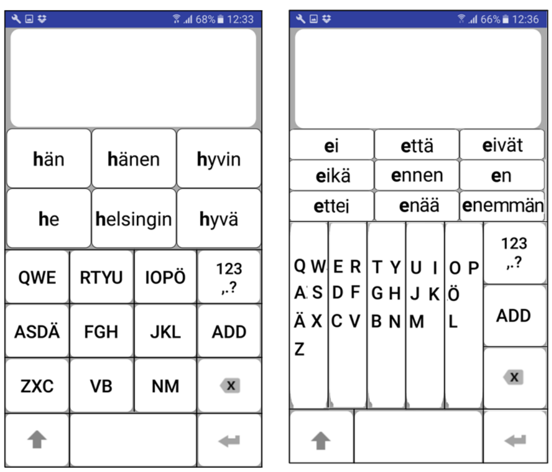


Figure 5. Overview of *Touch-WLM*. The model is parametrizable to present individual differences. The model has a decision loop that controls keystroke-level and word-level responses. If the user makes a mistake, speed–accuracy tradeoff (SAT) is changed to lower error rate. If the user has typed l letters, eyes will be shifted to the word prediction list to check if the typed word is there. Also, text display is checked and compared against the reference word.



(a) (b)

Figure 4. Example of some keyboard layouts belonging to the design space: (a) keyboard with 3×3 grid and (b) layout with 5×2 grid

Touch-WLM builds on two modeling approaches: first, the tradition of keystroke-level models (KLMs) [7] and, second, rational analysis [2]. By combining the two, we produce a model of how a user with different abilities might adapt to the task of text entry. For example, a person with impaired eye movements may want to look at the text display to ensure if the text is correct.

In keystroke-level models, task performance is modeled as deterministic sequences of mental actions and responses. Further, KLM assumes one way of executing a task. This task is broken down according to three categories of *operations*: physical, mental, and system. Physical operations include pointing, keystroking, homing, and drawing. Mental operations refer to events like recalling a command name or verifying that an answer is correct. System operation is system response time, the time spent waiting. These operations are counted and the times spent in each are estimated using guidelines and look-up tables. Task completion time is then their linear sum.

To overcome the issue of rigid task execution, KLM builds on work on rational analysis. Rational analysis refers to modeling human performance as optimal adaptation. It assumes that there are multiple degrees of freedom in action, and that after repetitive exposure users performance becomes closer and closer to optimal behavior. More formally, we want to pick strategy $s \in S$ that maximizes user performance. In our case, ”optimality” is defined in terms of words per minute (WPM) achieved with some acceptable proportion of errors. Using rational analysis, our model picks the best way to move the fingers and the eyes. In particular, a user typing very fast might have to spend relatively more time correcting errors than a user typing slow, for example due to issues of visual acuity. However, just how fast one should type depends on the probability of errors and the cost of correcting them. *Touch-WLM* tries to find the optimal speed–accuracy control point for a user.

Another strategic issue *Touch-WLM* solves is *when* to look at the text display. Given the fact that touchscreen keyboards lack tactile feedback, tapping the keys requires visual gaze. On the other hand, assuming that users do not always notice when they make an error, they must look at the text display once in a while to ensure there are no errors. They may also not know when to look at the word prediction list (WPL). How often should one look at the text display depends on individual abilities as well as the statistical distribution of ambiguity in the language corpus.

Overview of task model

Touch-WLM calculates how long it will take for a given individual ($M(\theta)$) to type a given word with a given design (D). It captures individual differences in typing speed by utilizing a model the human visual system, and a model for finger speed–accuracy tradeoff, as well as two variables describing behavioral strategies. A task model is followed:

1. Type l letters by
   (a) attending and encoding target key with eyes
   (b) moving finger to the key position and touching the key
2. If there was a typing error after typing l letters,
   (a) move finger to backspace button and touch it, calculating movement time with WHo model with maximised accuracy;
   (b) repeat backspace press as many times as necessary;
   (c) repeat step 1, i.e., type the letters again
3. If the correct word appeared in the word prediction list after l letters,
   (a) attend words in the prediction list one at a time
   (b) if the target is there, select it
   (c) if not, continue typing and finish the word

Eye movements

The model for attention shifts, encoding, and eye movements, follows the EMMA integrated model of eye movements and visual encoding [30]. The time it takes to encode a key is

$$T_e = E_K \cdot [-log(f)] \cdot e^{e_k \cdot \epsilon}, \tag{1}$$

where E_K and e_k are constants, f is the frequency of the object (e.g., monogram frequency), and ϵ is the eccentricity, measured as the distance of the target from current eye fixation (in degrees). Because encoding time increases exponentially as the function of eccentricity, the visual system may initiate a saccade to get closer to the target:

$$T_s = t_{prep} + t_{exec} + d \cdot t_{sacc}, \tag{2}$$

where t_{prep}, t_{exec}, and t_{sacc} are constants related to the human visual system, and d is the distance to be covered by the saccade in degrees. If the encoding time calculated in (x) is less than t_{prep}, then the target is encoded without the eyes moving from the previous targets. If not, then the remaining encoding is conducted after the saccade.

Pointing

After the model has encoded the target key, it moves a finger from the key on which it was previously. The finger movement time (x) and accuracy (y) calculations use WHo model [19]. The important feature of the WHo model is that it presents the speed–accuracy tradeoff (SAT) of pointing as a strategic curve:

$$(y - y_0)^{1-m_\alpha}(x - x_0)^{m_\alpha} = m_k, \tag{3}$$

where m_α and m_k are individual parameters to be assessed. The shape of the curve depends on individual ability, but the choice of being accurate with the cost of speed, of being fast with the cost of accuracy is done by the individual. While the WHo curve is asymptotic with global (not individual) limits, everybody has their own individual limits on how fast their finger can get (WHo$_{max}$), or how accurate they can maximally be (WHo$_{min}$). These parameters are evaluated individually.

Strategy

In addition to visual search and finger movement, individual ability in typing is affected by cognitive aspects, such as knowledge of the keyboard layout, speed of proofreading the typed text, and the ability to do multitasking between finger and eye movements. However, as will be shown below, the inclusion of such cognitive aspects into a model of touchscreen typing is difficult and requires further research into these topics.

However, we identify here two cognitive processes, called *confirmation time* $t_{confirm}$ and *visual key search time* s_{key}, which are currently left as individually fixed parameters.

The two free parameters of the model, l (how many letters are typed before checking it for errors and optionally looking for the word in the word prediction list) and *finger accuracy* m_a, are assigned based on the language corpus. The model simulates typing the words in the corpus with different parameter values, iterating through values 1-5, and accuracy values as given by the individually assigned WHo_{min} and WHo_{max}. The best combination of l and m_a are used as the best individually achievable typing performance. Because this last step of finding the best typing strategy, we name the model *Touch-WLM*.

Table 1 provides an inventory of all parameters that are used to describe differences among individuals and tasks in *Touch-WLM*. Informed by present knowledge of effects of aging, we can now explore the consequences of changing these parameters.

OPTIMIZATION

The possibilities of the ability-based optimization approach can be explored by investigated how changing the model parameters changes the optimal layout, given a parameter space. In this work, we discretized each design variable to obtain a search space that can be exhaustively covered. Here, we present comparison results for text entry rates of designs built for better finger speed, visual search time and proofreading

Table 1. Individual abilities modeled by *Touch-WLM*

Variable	Explanation	Domain
Eye movements		
e_K	Encoding time	Foveal encoding
e_k	Eccentricity factor	Parafoveal encoding
t_{prep}	Saccade preparation	Oculomotor command
t_{exec}	Saccade execution	Oculomotor command
t_{sacc}	Saccade velocity	Oculomotor performance
Motor performance		
m_k	Total resource	Motor performance
m_α	Speed–accuracy bias	Motor performance
Strategy		
m_a	Finger accuracy	Motor strategy
l	Letters before proofing	Cognitive strategy
Constants		
s_{key}	Search time for key	Visual search
$t_{confirm}$	Backspace confirmation	Thinking

time and the *baseline* (QWERTY layout). The design parameter space is described in Table 2 below.

Mean parameter values for the young and the old adults group (YA and OA) with the layout and baseline are displayed in Table 3. These parameters were obtained empirically WHo-min and -max are multiplied by 1000 to obtain the parameters for the model (easier to handle integers). Also, in the model, WPL reading and proofreading are both done at lth letter.

Optimization was carried out using exhaustive search.

RESULTS

This section reports our first results. We emulated multiple user groups and present here four of them (Figure 6) with their final designs.

Effects of decreasing finger speed

Our first exercise emulated a user with decreasing finger speed. This corresponds to the persons having tremor and perkinson's. We found that decreasing finger accuracy (m_a) negatively affects baseline. Larger keys are better in this case. Setting m_k to a large value (1.0) (low finger SAT resources), the layout displayed (Figure 6(a)) improves the WPM over baseline by 13.83% to 2.21. In addition, adjusting the m_α,

Table 2. Design factor value ranges in design optimization

Parameter	Range
Number of rows in the prediction list	1–5
Elements in each row of the prediction list	3
Row height	0.03%–0.07%*
Number of rows in text display area	2–7

* = represented as percentage of the display height (in pixel)

Table 3. Model parameter values

Parameter	YA mean	OA mean	Baseline	Variable
EMMA(s)	0.0134	0.0135	0.007	t_{sacc}
EMMA(p)	0.292	0.326	0.333	t_{prep}
WHo-k	0.116	0.138	0.126	m_k
WHo-a	0.616	0.681	0.577	m_a
WHo-min	0.00613	0.00714	7*	
WHo-max	0.0753	0.0538	150*	
Proofing	2.71	2.87		l
Bspace decide	0.781	1.43	1	$t_{confirm}$
Vis search (ms)	1066	1401		s_{key}

* = spread

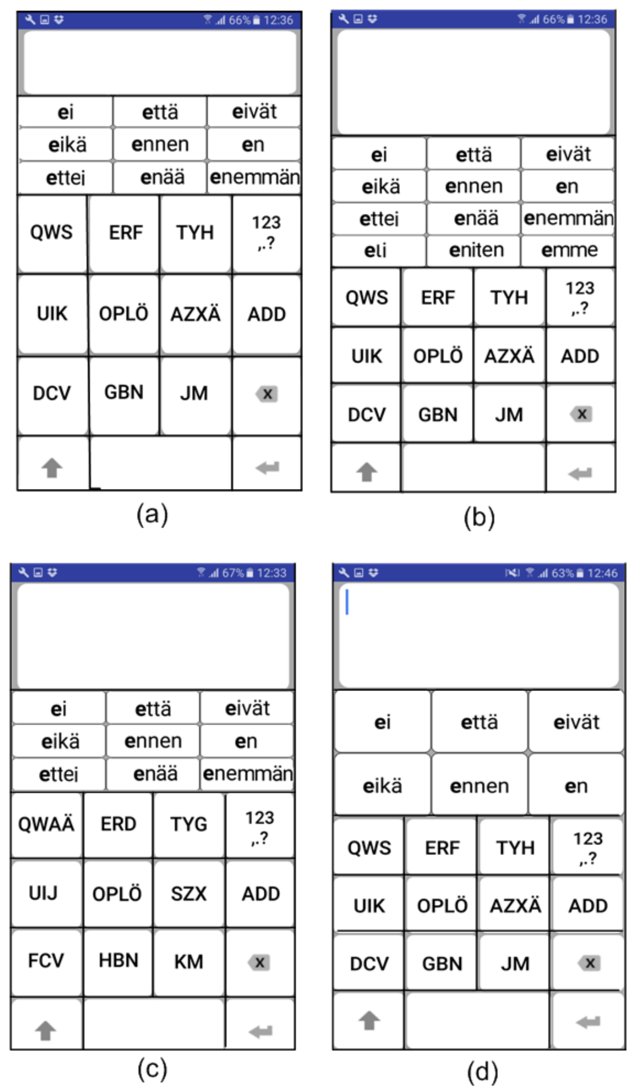


Figure 6. We design four keyboard layouts supporting several abilities: (a) this layout is designed for people who has essential tremor or parkinson's, (b) this layout is suitable for incurring lesser visual search time to the people who have prior knowledge about the layout, (c) and (d) these layouts support in achieving less proofreading time while typing, specially for users having reading disabilities, i.e. dyslexia.

i.e., the finger strategy weight parameter, between the extremes $[0.1, 0.9]$ does not change the overall result.

Effects of decreasing visual search ability

Our second exercise emulated a user with decreasing visual search ability. This corresponds to the people who have prior knowledge of the layout. Increasing the time it takes for the individual to locate a given key changes the optimal layout: if it takes a long time to search for a key, a keyboard with a large word prediction list is preferable. Increasing visual search time from $0.0s$ to $1.0s$ decreases the predicted WPM of the baseline layout from 15.7 to 7.5. Using the layout displayed in Figure 6(b) improves the WPM by 7.5% to 8.1.

Effects of slower proofreading time

Our third exercise emulated a user with decreasing proofreading time. This corresponds to the older people suffering with declining of cognitive processes during reading. Increasing proofreading time (initially setting as 2.6s) seems to benefit the grouped layout. However, if the proofing threshold l is raised, then the model chooses accurate SAT and proofreads rarely (because there are rarely errors with accurate SAT). This causes the baseline to be better again. Two layouts are designed (Figure 6(c) and 6(d)) which have improved WPM by 2.64% and 8.43% to 10.73 and 10.82, respectively, from the baseline layout.

DISCUSSION

This paper has presented first results towards extending ability-based optimization to account for age-related differences in computer use. Our long-term goal is a computational method to drive the differentiation of user interfaces based on individual abilities. In the future, those abilities could be either explicitly stated by the user (customization) or inferred from log data (adaptation).

As ability-based optimized keyboard layouts are designed considering specific abilities, the experiment with a keyboard requires recruitment of participants having deficiency in corresponding specific ability. Moreover, a prior study would be conducted to ensure the deficiency. For example, before the experiment with people having essential tremor, it is required to run the prior test to identify the tremor range of the participants. If the test reveals that participants, in spite of old, do not posses any tremor, then they are not allowed in the main experiment. The aim of the user study is to compare the user performance (mainly though text entry rate as WPM or CPS) of the design layouts with the baseline, which is QWERTY layout.

The present paper has contributed toward solving two emerging problems in this space: First, we need to describe individual differences in predictive models. Previous work on ability-based optimization has been limited to motor performance and addressed other abilities via heuristics, if at all. There has been no systematic methodology to express individual differences in a psychologically plausible way. Therefore, to extend this approach beyond simple pointing tasks driven by Fitts' law, it is necessary to build models that directly incorporate factors that predict differences among user groups. Second, models need an account of *how* an individual with particular capabilities will interact. To this end, we have started to explore applications of computational rationality in this space. The results we presented here show that the idea of comparing parametric modeling with computational rationality can produce results that differentiate designs for user groups with different effects of aging.

We note two disadvantages to the parametric approach as challenges for future work. First, we presently lack operational definitions of design problems that match with available predictive models. Beyond this and the previous studies, existing models have not been expressed in such a way that individual differences can be parametrically expressed. Second, we lack predictive models that cover essential aspects of the large diversity of effects that impairments, aging, and individual differences can have. In the absence of such models, one may have to resort to heuristic approaches or drop some important design considerations entirely.

As a final note, we find it tremendeously important to investigate methodology that allows designers to go beyond the failed "one design fits all" approach. The non-individualization and mis-individualization of UIs is a major issue. Without UI designs that better support individual ways of using smartphones, the aging population will be hampered in their ability to participate in the society.

ACKNOWLEDGMENTS

The project has received funding from the JST and Academy of Finland under the project "User Interface Design for the Ageing Population" as an activity of FY2014 Strategic International Collaborative Research Program (SICORP).

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