There is more to Typing than Speed: Expressive Mobile Touch Keyboards via Dynamic Font Personalisation

Daniel Buschek[1], **Alexander De Luca**[1,2], **Florian Alt**[1]
[1]Media Informatics Group, University of Munich (LMU); [2]DFKI GmbH, Saarbrücken, Germany
{daniel.buschek, alexander.de.luca, florian.alt}@ifi.lmu.de

ABSTRACT

Typing is a common task on mobile devices and has been widely addressed in HCI research, mostly regarding quantitative factors such as error rates and speed. Qualitative aspects, like personal expressiveness, have received less attention. This paper makes individual typing behaviour visible to the users to render mobile typing more personal and expressive in varying contexts: We introduce a dynamic font personalisation framework, *TapScript*, which adapts a finger-drawn font according to user behaviour and context, such as finger placement, device orientation and movements - resulting in a handwritten-looking font. We implemented *TapScript* for evaluation with an online survey (N=91) and a field study with a chat app (N=11). Looking at resulting fonts, survey participants distinguished pairs of typists with 84.5% accuracy and walking/sitting with 94.8%. Study participants perceived fonts as individual and the chat experience as personal. They also made creative explicit use of font adaptations.

Author Keywords

Mobile; Touch Typing; Font Personalisation

ACM Classification Keywords

H.5.2. Information Interfaces and Presentation (e.g. HCI): Input devices and strategies (e.g. mouse, touchscreen)

INTRODUCTION AND RELATED WORK

We often enter text on mobile devices, for example for search queries and chats. To improve efficiency, the HCI community has addressed speed and error rates [10]. Fast and accurate typing is clearly desirable. Some usages, like casual communication, may also benefit from qualitative information and context, currently conveyed in discrete markup choices (e.g. CAPS, *italic*), emoticons, and context hints (e.g. has been seen/read; sent from device/place X). In contrast, this paper explores facilitating expressiveness by indicating personal behaviour and context directly in the text via dynamic fonts.

Our approach takes inspiration from handwriting, which is usually regarded as highly individual [13] (e.g. signature) and context-sensitive – we write differently on a shaky train ride

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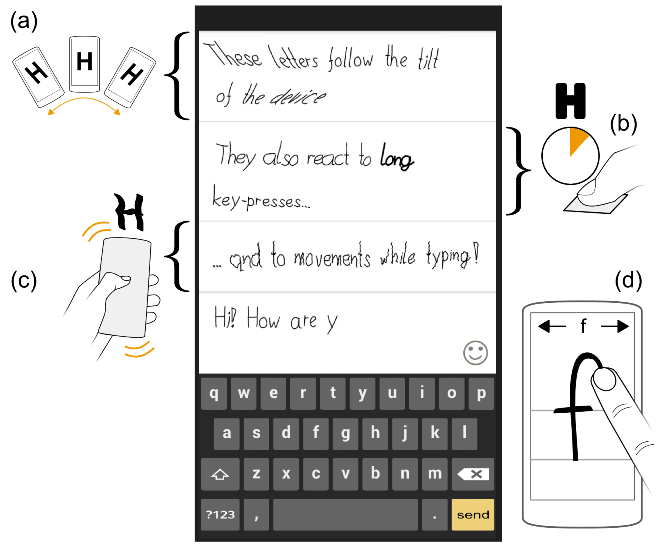

Figure 1. ***TapScript*** **font personalisation concept and prototype chat application. This figure showcases font adaptations: skewing characters according to device rotation (a), adapting line thickness to key-hold time (b), and adding noisy transformations according to device movement (c). Our chat app applies these adaptations to a finger-drawn font, recorded as shown in (d). Adaptations can occur implicitly (e.g. typing while walking) or they are triggered explicitly by the user (e.g. tilting for *italic*). We further model users' individual touch and typing behaviour, updated after each keystroke, to add slight personal variations to their base fonts.**

than at a table at home. To enable such influences for text composed on mobile devices, we personalise each character's appearance based on user behaviour and context at each keystroke (Figure 1).

Kienzle and Hinckley [9] segmented strokes to enable drawing overlapping characters at the same screen location for text messaging on a smartphone. Their study showed that users liked the personal aspect and the "*simple/fun experience*". This supports the motivation for our work. However, we ask users to draw characters only once, storing a personal finger-drawn font. We then dynamically alter this font based on typing behaviour and context-specific influences. Our approach can retain benefits of keyboards (e.g. less effort than finger writing, one-handed use).

Iwasaki et al. [8] mapped typing pressure to font-size when chatting with a laptop. Similarly, we adapt stroke thickness based on typing features, but for mobile on-screen keyboards. In desktop environments, chat text was animated (e.g. jumping words) to convey selected emotions [2] and physiological signals from on-body sensors [14]. Our mobile approach only uses data from device sensors and no animations.

Hoggan et al. [6] proposed a system to augment phone calls with a pressure-based channel for non-verbal information, such as emotions. Squeezing their prototype phone triggered vibration at the partner's phone. We instead target mobile texting and estimate pressure from touch input without requiring additional hardware.

We contribute: 1) a dynamic font personalisation concept for mobile touchscreen devices, and 2) its implementation in a chat app, evaluated in an online survey and a field study.

CONCEPT

To put our concept into context, Table 1 shows input methods and output styles for manual mobile text entry. We fill the gap: typing with handwritten-looking output. However, it is not our goal to precisely replicate actual handwriting, we only take it as an inspiration for possible font adaptations.

Foundation: Elements of Writing Style and Execution

Our approach considers the 21 *discriminating elements of handwriting* by Huber and Headrick [7]. We review them to identify influences for fonts. This results in five font adaptations, derived by transferring writing elements to typing.

Overall, Huber and Headrick distinguish two groups: *elements of style* and *elements of execution*. To select suitable influences for font adaptation, we match this classification with our adaptation goals – personalisation and context:

Elements of style can capture user-specific behaviour, such as the personal style of certain letters. We chose the elements *class of allographs*, their *design*, *dimensions*, and *slant/slope*. Examples are listed with the adaptations in the next section.

Elements of execution can capture context-based influences, for example less precise lines due to body movement while writing/typing. Here, we consider these elements: *diacritics and punctuation, embellishments, line continuity, line quality, pen control,* and *writing movement*.

This selection includes half of the elements of Huber and Headrick. They also list general *natural variation*, which we consider, too. We excluded elements across letters (e.g. connections/spacing between letters/words, abbreviations), since we aim to limit adaptations to one character at a time, so that users can see the full and final effect after each keystroke.

Realisation for Typing: Font Adaptation

TapScript aims to realise elements of visual variation similar to those mentioned above – for typing instead of writing. To achieve this, we propose five font adaptations ($\mathbf{A}_i$):

$\mathbf{A}_1$: *Adaptation based on Initial On-Screen Writing*

This adaptation is based on the handwriting elements *class of allographs* (e.g. block vs cursive characters), *design of allographs* (e.g. ɑ vs a), *dimensions* (e.g. proportions of elements of letters), *diacritics and punctuation* (i.e. their presence, style, location), and *embellishments* [7].

To allow for such individuality in typing as well, we use a "handwriting sample". In an enrolment phase, users draw the alphabet on the empty screen (Figure 1d). This finger-drawn font is then used by our system for further adaptation.

input/output	static font	handwritten
typing	normal keyboard	this paper: *TapScript*
writing	handwriting recognition	on-screen writing

Table 1. Design space for manual text input methods (rows) and output styles (columns) on mobile touch devices. This paper fills the remaining gap: input via typing with output which visually resembles handwriting.

$\mathbf{A}_2$: *Adaptation based on Individual Touch Behaviour*

This adaptation is based on Huber and Headricks's *writing movement* (defined as variants in the action of the pen), *natural variation* in writing habits, and *pen control: pen hold*, meaning the grasp of the pen by the hand [7].

To reveal natural variations in movements during typing, we adapt the font based on models of touch targeting behaviour [4, 15, 16, 17], continuously updated after each keystroke. This results in small allograph variations (e.g. no two "a" look exactly the same). These adaptations can also reflect movement, since touch targeting changes when walking [1, 5].

Moreover, since these touch models are hand posture-specific [3, 4], they also capture influences in analogy to *pen hold* - the grasp on the mobile device influences the font.

$\mathbf{A}_3$: *Adaptation based on Device Movement*

This adaptation realises Huber and Headrick's *line quality* element, described as the regularity of strokes, varying between controlled, smooth lines and tremulous ones [7].

To reveal line quality based on mobile typing behaviour, we use the accelerometer sensor to capture "tremor" and to influence the font accordingly: Shaky device movements during typing lead to noisy and distorted lines (Figure 1c).

$\mathbf{A}_4$: *Adaptation based on Device Orientation*

This considers the elements *slant/slope* (i.e. angle of letters relative to writing baseline) and *pen control: pen position* (i.e. orientation of pen relative to paper or baseline) [7].

We realise similar visual variations for mobile typing by considering device orientation instead of pen orientation: Letters are skewed according to the tilt of the device (Figure 1a).

$\mathbf{A}_5$: *Adaptation based on Touch Pressure/Duration*

This adaptation implements the elements *pen control: point load* (i.e. vertical force at the tip of the pen), and *line continuity* (i.e. pen stops, lifts, retracings) [7].

Here, we consider that writers can vary pressure with their pen on the paper, or spend more time with a single line through retracing or slower movement. For on-screen keyboards, we can realise such variations by changing line thickness based on touch pressure and duration (Figure 1b).

Implicit and Explicit User Behaviour

The described influences can vary implicitly over time or due to the context, but users may apply them explicitly as well. For example, a device could be tilted due to body posture (e.g. lying on a couch). On the other hand, the user could actively tilt the device to influence the font (e.g. to write *italic*).

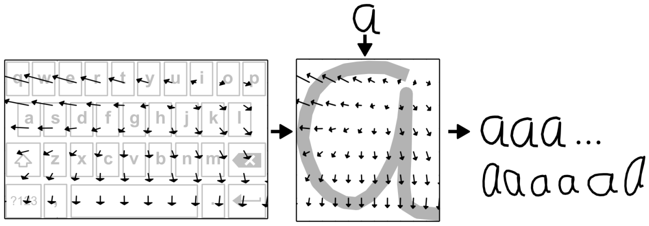

Figure 2. Implicit character variations based on typing behaviour: To render users' finger-drawn fonts in a less static and more natural look, we map touch-to-key offset patterns (arrows) from keyboard-space (left) to character-space (right). The character's points are then translated accordingly. This results in variations of the base font, as shown here for one user's letter "a". During actual typing, updating the behavioural model after each touch leads to smooth transitions (top row examples).

TECHNICAL DESCRIPTION

We next describe technical details of the adaptations outlined above. In general, we use Gaussian Processes (GPs, [11]) and sigmoid functions to influence each character with sensor values captured at the time of the corresponding keystroke.

Translating Points based on Typing Offsets

We use GP regression to describe individual offset patterns across the keyboard [16, 17]: These models learn a function to map touch locations to the key centres, trained on the current touches while the user is typing. Since we do not know the ground truth intended keys, we simply measure the offset to the key on which the touch occurs. We then map the resulting regression patterns from keyboard-space to character-space ($\mathbf{A}_2$). Hence, offset models are interpreted as non-linear translation operators for the font (Figure 2).

We update the mapping after each touch by re-training the GP model on the history of the last h touches (study used h=15). By changing the models' hyperparameters (see related work for more details [11, 17]), we can influence the degree of non-linearity, and thus the degree of possible distortion.

We chose these models and this mapping for two specific reasons: First, offset models are individual [17] and context-dependent (e.g. hand posture [3, 4]). Thus, they alter the font differently for different users and contexts, supporting our adaptation goals with a well-researched model. Second, we aimed to produce a more "natural" look with *subtle*, *implicit* allograph variations: As in handwriting, these can happen beyond the writer's direct control (e.g. natural hand tremor, limited precision and repeatability of human motor system, imprecisions due to body movement). Hence, we chose a mapping that passes on influences of user and context from models to font without being openly obvious to direct control (compared to, for example, tilting the device to tilt the font).

Feedback from our field study participants suggests that they indeed understood the resulting variations as an integral part of the handwritten look, as intended – but only as long as these variations stayed subtle (see field study section).

Adding Noise based on Accelerometer Readings

We add random translations of font points based on device movement ($\mathbf{A}_3$). We measure the 3D acceleration vector a's magnitude $a_m = ||a||$, and compute its first derivative a'_m over time (i.e. change of magnitude), processed as follows:

$$n(a'_m) = \frac{n_{max}}{1 + e^{-a_s(a_m - a_o)}}$$

Here, $n(a_m) \in [0, n_{max}]$, a_o sets the magnitude required for 50% noise, and a_s sets the slope of the increase. Noise is then applied via point-wise translation: $x' = x + n(a'_m)\varepsilon$, with Gaussian noise ε, and respectively for y. We average the acceleration over a small time frame to improve the effect's stability. This may also be used explicitly by "charging" the font with noise via shaking prior to typing.

Skewing Characters based on Gyroscope Readings

We skew letters based on the device's angle v around the axis "coming out of the screen" ($\mathbf{A}_4$). The horizontal skew s is:

$$s(v) = \mathrm{sign}(v) \frac{s_{max}}{1 + e^{-v_s(|v| - v_o)}}$$

Note that $s(v) \in [-s_{max}, s_{max}]$, v_o defines the tilt required for 50% skew, and v_s sets the slope of the increase. The resulting skew is applied via point-wise translation: $x' = x + (0.5 - y)s(v)$, assuming normalised coordinates (i.e. $x, y \in [0, 1]$). To improve stability, we average the orientation v over a small time frame leading up to the keystroke.

Changing Line Thickness based on Key Hold-Times

To implement $\mathbf{A}_5$, we render thicker lines for longer key presses. We chose hold-time for our prototype, since pressure (as estimated by the Android API) was less predictable and some devices only offered a few discrete values. Formally, we map hold-time t to thickness b:

$$b(t) = b_{min} + \frac{1}{1 + e^{-t_s(t - t_o)}}(b_{max} - b_{min})$$

Here, $b(t) \in [b_{min}, b_{max}]$, t_o sets the time required for 50% thickness above b_{min}, and t_s defines the slope of the increase.

ONLINE SURVEY

To evaluate our font personalisation approach, we conducted an online survey and a field study. We first describe the survey: Here, we showed participants images of sentences typed with our prototype app to assess the general potential of our approach regarding two key aspects, namely revealing 1) context and 2) personal characteristics.

Survey

To create the images for our survey, five separate participants typed two sentences – each one three times – in two contexts (sitting, walking) in a prototype app on a Nexus 5 in a single session in the lab. The app displayed the sentences at the top, a text entry field in the centre, and the keyboard at the bottom. Parameters were determined experimentally by the authors with a pre-test on a few phone models. We chose two sentences (shown in Figure 3 and 4) which reveal the complete alphabet without entering a lot of text. This also reduces reading time for the participants of the survey.

The survey itself then asked participants to compare these images. Participants were left ignorant of our concept: we did not reveal that sentences were not really written by hand. Besides demographic data, there were two main blocks of questions: *context* and *identity*. Both the order of the blocks, as well as the order of questions within each block was randomised between participants.

All questions asked participants to choose between two answers, and to indicate the confidence in their answer. Therefore, we provided a seven-point scale, with "high confidence" at each end, and a "don't know" option in the centre.

In the *context* block, each question showed an image of both sentences entered by the same person, asking which one was created while walking. Figure 3 shows an example. For each user, both sentences were included both as sitting and walking, resulting in a total of ten questions in this block.

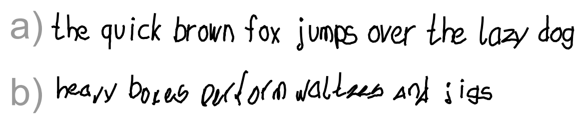

Figure 3. Example question from the *context* block: *"Which of these sentences was written while walking around?"* Here, the correct answer is *b)*. In general, moving around while typing leads to less precise touches and more device movement, reflected by less precisely drawn letters.

In the *identity* block, each question showed an image of both sentences. Participants were asked whether both sentences were written by the same person. Figure 4 shows an example. Since there were $\frac{5\times4}{2} = 10$ pairs of different users, ten questions had the correct answer "no" (i.e. both sentences were entered by different individuals). Complementary, there were five questions with the correct answer "yes" (i.e. both sentences were entered by the same person).

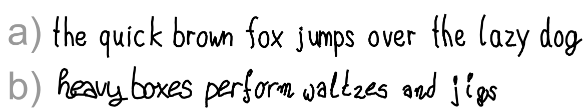

Figure 4. Example question from the *identity* block, asking: *"Was sentence a) written by the same person as sentence b) ?"* Here: *"no"*.

Results

Over 19 days, 91 participants completed the survey (mean age: 26, range: 18-50). We count answers as "correct" if any of the confidence levels for the correct one was selected.

Comparing two sentences from the same user, participants correctly identified them as belonging to the same individual in 92.7% of the cases. Two sentences from different users were correctly identified as belonging to two individuals in 80.4% of the cases. Overall, participants assessed identity in these questions with an accuracy of 84.5%. The "don't know" option accounted for 3.3% of all answers. Moreover, 89.1% of correct answers were selected on the second (27.3%) or third (61.8%) confidence level (of the three possible levels).

When they were asked which one of two sentences from the same user was created while walking, participants gave the correct answer in 94.6% of the cases. Here, 94.8% of correct answers were at the second (18.5%) or third (76.3%) confidence level. 2.6% of all answers were "don't know".

In summary, when comparing two sentences, participants answered correctly in most cases. Two of the typists created rather similar base fonts via finger writing, explaining the lower accuracy for identification than context. In a free text comment field, some survey participants mentioned this and explained their strategies (e.g. distinguishing by curly f).

These results show that our adaptation concept produces fonts which allow for visual assessment of basic contexts and individual characteristics. This supports our goal of creating personalised and context-rich fonts. Note, that more text for comparison is available in real applications (e.g. chat history; someone starts to walk during chatting).

FIELD STUDY

We implemented *TapScript* in a group chat application for a field study to complement the survey with an evaluation with participants using our concept in their everyday life.

Participants

We recruited 11 participants (5 female; mean age: 25, range: 20-27) in 5 groups of 2-3 friends, which usually chatted together on their phones. Each received a €15 gift card.

Apparatus

Our Android application allowed users to enter a name (displayed with each message) and to create their base font by drawing each character on the screen, one at a time. Users could redraw individual characters of their base font at any time during the study. In the chat view (Figure 1), a custom keyboard was used to measure the required touch features. Its design was kept close to the current default Android keyboard (Nexus 5), but without auto-correction or word suggestions. We also added a "smiley drawing" function to create and insert small custom drawings into the messages. On its first launch, the app showed a tutorial to explain its font adaptation functionality, the study procedure, and how to draw the initial font with the finger. This information could be displayed again at any time via a help button.

Procedure

Participants were given a web link to download and install our app on their own phones. They were instructed to chat with their group members for at least one week (four groups), up to three weeks (one group). Afterwards, we invited each group to our lab for semi-structured interviews.

Results

We chose a qualitative evaluation to explore the potential of our concept through insights into participants' impressions and contexts of use, and to inform further improvements. On average, each participant created about 44 messages over the week. We refer to individual participants as P_i.

Personalisation

Regarding their overall chat experience, participants said that it was more personal ($P_1, P_2, P_5, P_6, P_7, P_{10}, P_{11}$), diversified ($P_3, P_5$), creative ($P_5, P_9$), and expressive ($P_7, P_{10}, P_{11}$), compared to their usual messenger apps. For example, P_6 said that "*it is overall just much, much more personal*".

All participants liked our concept of handwritten-looking personalised fonts, and perceived them as individual. This matches the results from the survey. For example, P_1 showed us that the font looked similar to a sentence written on paper during the interview. P_3, P_4 and P_5 compared their fonts and concluded that "*naturally, everyone has his own way of writing the letters*" (P_5).

P_6 and P_7 liked that they could recognise each others (font) writing, although it differed from their actual handwriting. P_8, P_9 and P_{11} expressed similar views.

Several participants (P_1, P_3, P_5) mentioned that the handwritten look facilitated a more colloquial style, compared to other chat apps. For example, P_1 said that *"it was a bit more like talking to each other"*.

All groups said they would like to continue using our font personalisation concept for written mobile communication. P_2 and P_6 (different groups) suggested digital postcards/letters as further applications, *"because a card should always be written by hand, since it's something personal*" (P_2).

Contexts and Implicit Adaptation

Overall, the app was used at home (all P), on the go ($P_1, P_2, P_3, P_6, P_7, P_8, P_{10}, P_{11}$), at work ($P_4, P_8, P_{10}, P_{11}$), while eating ($P_4$), running ($P_{10}$), on a day trip ($P_8$), and during a holiday trip (P_{10}, P_{11}).

Some of our participants used the app on the subway ($P_2, P_3, P_6, P_7, P_{10}, P_{11}$). P_2 said that the font looked less regular there, and that sudden bumps led to too strong deformations. This user's group (P_1, P_2) then talked about the shaky ride in the chat. The other participants reported no overly strong adaptations on the subway, but P_3 mentioned more typing errors there due to the motion and the lack of auto-correction in our prototype.

Some participants mentioned that typing while lying on the side showed in the font's tilt (P_3, P_5, P_6, P_7, P_9). P_{10} recognised walking in P_{11}'s messages. One of P_3's messages contained a short distorted part, which caused P_5 to wonder whether P_3 had fallen or dropped the phone.

Explicit Adaptation

Adaptations were used explicitly to explore the functionality of our app and concept (all P), to reflect a word's meaning (P_1 wrote "upwards" tilted upwards, P_{10} wrote "fat" with thick lines) and to complement drawings (P_5 added a wavy tail of differently tilted "i"s behind a drawn insect). For a day, P_6 swapped some characters in the base font, and P_9 (different group) mirrored the letters, both in order to playfully "encrypt" their messages.

Regarding legibility, some said that they took care to avoid mistyping (P_2, P_3, P_6) or tilting too far (P_1, P_5, P_6, P_7, P_9) in some situations (e.g. when lying down).

Further Feedback and Suggestions

When asked about possibilities for future improvements, most participants mentioned further common features of chat apps, such as notifications or a contact list.

We also explicitly asked what they liked about the app and its differences to other chats: Participants highlighted the personalised font (all P), the font creation system (P_1, P_6, P_7), drawing and sending smileys/images (all P), explicitly influencing the font (P_7), and the in-app tutorial (P_1, P_2).

Their feedback also suggests more control over adaptations: stronger limitations on the tilt for some cases (P_5, P_7), affecting line thickness per word (P_3) or with a different feature than hold-time (P_2, P_4, P_9), ensuring no overlap for thin letters (e.g. "i", P_5), and explicit influences of typing speed (P_7). Offset-based adaptations were sometimes perceived as too strong and in consequence hard to explain (P_1, P_2, P_{10}, P_{11}), due to their implicit nature.

On the other hand, users also suggested additional dimensions of adaptation: font-size (P_3, P_8, P_9), colour (P_1, P_2, P_8, P_9) and writing animations (P_4). They also mentioned further context data: weather (P_1, P_6, P_7), location (P_6), lighting conditions (P_1, P_7), and volume of surrounding noise (P_7).

SUMMARY AND DISCUSSION

Our study shows that *TapScript* enables expressive typing in chats: Participants liked to send and receive messages written in personal fonts, and explored and applied influences explicitly and implicitly. Fonts were perceived as individual and distinguishable in both field study and survey. To summarise our results, we discuss them regarding three key areas: impact, interpretation, and intended usages.

Impact of Written Look vs Adaptations

The fonts resulting from our concept differ from usual fonts in two ways – a handwritten look and adaptations. In our interviews, we found that the written look led to general impressions such as individual, intimate, and casual.

In contrast, adaptations were recalled regarding specific situations. They made participants think about the contexts of their chat partners (e.g. subway ride). However, some participants also wondered about the underlying mappings (e.g. how exactly was it influenced by typing behaviour).

Interpreting Adaptations

Our evaluations show that fonts can be suitably influenced by context based on device orientation and movement. Survey participants correctly interpreted influences of walking compared to sitting in most cases, without further knowledge of our concept. Participants in the field study also noticed changing influences in the font in a variety of situations.

However, implicit adaptations were sometimes perceived as too strong (e.g. tilt while lying on the side), or not clear enough (e.g. reflecting typing speed).

We can address this by tweaking the adaptation parameters in our framework (see technical description), for example limiting the tilt, the amount of noise, and the degree of nonlinearity in offset models. Feedback suggests that users would also like to control adaptation settings themselves.

Adaptation Usage

In our field study, explicit use of font adaptations was explored for novelty, to emphasise a word's meaning and for other playful and creative effects.

Our participants' feedback indicates that they would not want to use font adaptations with everyone (e.g. not in business emails). On the other hand, all participants said that they would like to continue using our concept in their personal mobile communication.

LIMITATIONS

Novelty: We conducted a field study over one to three weeks. Our participants' views might be biased due to the novelty of our concept. A longer study could investigate usage and the users' views, when the concept's novelty wears off.

Privacy: Users might not want to share personal fonts with strangers or public audiences. We propose to only enable personal fonts with user-selected partners (i.e. a friends list). For other recipients, the text can be rendered in a normal font.

Legibility: Some participants said that they tried to type carefully, or that they re-entered text to avoid too strong adaptations (e.g. due to sudden movements, like typing while standing up, P_{11}). To improve legibility, we suggest to consider limiting adaptation strengths per character, word or sentence.

Speed: P_9 felt slower due to checking legibility. Others felt not slower than usual (P_8), or valued typing carefully as a positive training effect (P_5). No one reported speed as problematic. Nevertheless, a lab study could quantitatively compare speed with and without font adaptations.

CONCLUSIONS AND FUTURE WORK

Typing is a common and important task on mobile devices. Research has often addressed aspects of efficiency, like speed and error rates. In contrast, this paper focussed on expressiveness: We presented *TapScript*, a dynamic font personalisation framework, which adapts the visual appearance of characters based on the typist's behaviour and context at each keystroke.

In contrast to current meta-information in texting (e.g. CAPS, context hints: message sent from device/place), our concept enables subtle indications of personal behaviour and context directly via the font itself. Hence, *TapScript* provides and explores new possibilities for expressive mobile text entry.

An online survey revealed that resulting fonts are distinguishable between users and basic contexts. A field study with a chat app showed positive feedback on personalisation and expressiveness for casual communication. In contrast to on-screen writing, *TapScript* retains the benefits of keyboards (e.g. one-handed use, word suggestion/correction, no stylus). To conclude, we highlight insights which inform further work on personalised, context-adaptive mobile text entry:

- Fonts with letters drawn with a finger on the screen convey individual, identifiable characteristics, similar to writing.
- The handwritten look is perceived as casual and personal, but potentially less legible than usual fonts.
- Adaptation possibilities elicit creative usages in chats.
- Implicit adaptations need to stay understandable, and consistently subtle or adjustable: users like to feel in control.
- Control over adaptations should consider several levels: in general, in specific situations, and for specific recipients.

Based on our insights, we plan to improve concept and app for a larger, long-term deployment. Control over adaptations can be improved with parameter pre-sets, for example presented as virtual pens. We will also investigate further context influences as well as adaptations based on temporal models [12].

REFERENCES

1. Joanna Bergstrom-Lehtovirta, Antti Oulasvirta, and Stephen Brewster. 2011. The Effects of Walking Speed on Target Acquisition on a Touchscreen Interface. In *MobileHCI 2011*. 143–146.
2. Kerry Bodine and M. Pignol. 2003. Kinetic Typography-Based Instant Messaging. In *CHI 2003 EA*. 914–915.
3. Daniel Buschek and Florian Alt. 2015. TouchML: A Machine Learning Toolkit for Modelling Spatial Touch Targeting Behaviour. In *IUI 2015*. 110–114.
4. Daniel Buschek, Simon Rogers, and Roderick Murray-Smith. 2013. User-Specific Touch Models in a Cross-Device Context. In *MobileHCI 2013*. 382–391.
5. Mayank Goel, Leah Findlater, and Jacob O. Wobbrock. 2012. WalkType: Using Accelerometer Data to Accommodate Situational Impairments in Mobile Touch Screen Text Entry. In *CHI 2012*. 2687–2696.
6. Eve Hoggan, Craig Stewart, and Laura Haverinen. 2012. Pressages: Augmenting Phone Calls with Non-Verbal Messages. In *UIST 2012*. 555–562.
7. Roy A. Huber and A. M. Headrick. 1999. *Handwriting Identification: Facts and Fundamentals*. CRC Press.
8. Ken Iwasaki, T. Miyaki, and J. Rekimoto. 2009. Expressive Typing: A New Way to Sense Typing Pressure and Its Applications. In *CHI09 EA*. 4369–4374.
9. Wolf Kienzle and Ken Hinckley. 2013. Writing Handwritten Messages on a Small Touchscreen. In *MobileHCI 2013*. 179–182.
10. Per Ola Kristensson and Keith Vertanen. 2014. The Inviscid Text Entry Rate and its Application as a Grand Goal for Mobile Text Entry. In *MobileHCI 2014*.
11. C. E. Rasmussen and C. K. I. Williams. 2006. *Gaussian Processes for Machine Learning*. The MIT Press.
12. Y. Singer and N. Tishby. 1994. Dynamical encoding of cursive handwriting. *Biological Cybernetics* 71, 3 (1994), 227–237.
13. Sargur N. Srihari, Sung-Hyuk Cha, Hina Arora, and Sangjik Lee. 2002. Individuality of Handwriting. *Journal of Forensic Sciences* 47, 4 (2002), 1–17.
14. Hua Wang, Helmut Prendinger, and Takeo Igarashi. 2004. Communicating Emotions in Online Chat Using Physiological Sensors and Animated Text. In *CHI 2004 EA*. 1171–1174.
15. Daryl Weir, Daniel Buschek, and Simon Rogers. 2013. Sparse Selection of Training Data for Touch Correction Systems. In *MobileHCI 2013*. 404–407.
16. Daryl Weir, Henning Pohl, Simon Rogers, Keith Vertanen, and Per Ola Kristensson. 2014. Uncertain Text Entry on Mobile Devices. In *CHI 2014*. 2307–2316.
17. Daryl Weir, Simon Rogers, Roderick Murray-Smith, and Markus Löchtefeld. 2012. A User-Specific Machine Learning Approach for Improving Touch Accuracy on Mobile Devices. In *UIST 2012*. 465–476.