Behaviour-Aware Mobile Touch Interfaces

Dissertation

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vorgelegt von

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ABSTRACT

Mobile touch devices have become ubiquitous everyday tools for communication, information, as well as capturing, storing and accessing personal data. They are often seen as personal devices, linked to individual users, who access the digital part of their daily lives via hand-held touchscreens. This personal use and the importance of the touch interface motivate the main assertion of this thesis: Mobile touch interaction can be improved by enabling user interfaces to assess and take into account *how* the user performs these interactions. This thesis introduces the new term "behaviour-aware" to characterise such interfaces.

These behaviour-aware interfaces aim to improve interaction by utilising behaviour data: Since users perform touch interactions for their main tasks anyway, inferring extra information from said touches may, for example, save users' time and reduce distraction, compared to explicitly asking them for this information (e.g. user identity, hand posture, further context). Behaviour-aware user interfaces may utilise this information in different ways, in particular to adapt to users and contexts. Important questions for this research thus concern understanding behaviour details and influences, modelling said behaviour, and inference and (re)action integrated into the user interface. In several studies covering both analyses of basic touch behaviour and a set of specific prototype applications, this thesis addresses these questions and explores three application areas and goals:

1) *Enhancing input capabilities* – by modelling users' individual touch targeting behaviour to correct future touches and increase touch accuracy. The research reveals challenges and opportunities of behaviour variability arising from factors including target location, size and shape, hand and finger, stylus use, mobility, and device size. The work further informs modelling and inference based on targeting data, and presents approaches for simulating touch targeting behaviour and detecting behaviour changes.

2) *Facilitating privacy and security* – by observing touch targeting and typing behaviour patterns to implicitly verify user identity or distinguish multiple users during use. The research shows and addresses mobile-specific challenges, in particular changing hand postures. It also reveals that touch targeting characteristics provide useful biometric value both in the lab as well as in everyday typing. Influences of common evaluation assumptions are assessed and discussed as well.

3) *Increasing expressiveness* – by enabling interfaces to pass on behaviour variability from input to output space, studied with a keyboard that dynamically alters the font based on current typing behaviour. Results show that with these fonts users can distinguish basic contexts as well as individuals. They also explicitly control font influences for personal communication with creative effects.

This thesis further contributes concepts and implemented tools for collecting touch behaviour data, analysing and modelling touch behaviour, and creating behaviour-aware and adaptive mobile touch interfaces. Together, these contributions support researchers and developers in investigating and building such user interfaces.

Overall, this research shows how variability in mobile touch behaviour can be addressed and exploited for the benefit of the users. The thesis further discusses opportunities for transfer and reuse of touch behaviour models and information across applications and devices, for example to address tradeoffs of privacy/security and usability. Finally, the work concludes by reflecting on the general role of behaviour-aware user interfaces, proposing to view them as a way of embedding expectations about user input into interactive artefacts.

ZUSAMMENFASSUNG

Mobile Geräte mit berührungsempfindlichem Bildschirm ("Touchscreen") sind unerlässliche Alltagshelfer geworden, sei es zur Kommunikation, Informationssuche oder dem Erstellen, Speichern und Abrufen persönlicher Medien und Daten. Insbesondere Smartphones werden dabei oft als pesönliche Geräte betrachtet, die einem bestimmten Nutzer gehören und für diesen den individuellen Zugang zum mobilen digitalen Leben bedeuten. Diese persönliche Nutzung, kombiniert mit der zentralen Bedeutung des Touchscreens zur Interaktion, motiviert die zentrale Aussage dieser Dissertation: Interaktion mit mobilen Geräten mit Touchscreen kann verbessert werden, indem Nutzerschnittstellen in die Lage versetzt werden, zu erfassen und zu berücksichtigen *wie* der Nutzer Interaktionen damit ausführt. Diese Dissertation führt den Begriff "behaviour-aware" (d.h. "verhaltenssensitiv") ein, um solche Nutzerschnittstellen zu charakterisieren.

Diese verhaltenssensitiven Nutzerschnittstellen zielen darauf ab, die Interaktion durch die Verwendung von Verhaltensdaten zu verbessern. Solche Daten fallen bei der Nutzung ohnehin an, weshalb jegliche zusätzliche Information, die daraus abgeleitet werden kann, einen Gewinn verspricht. So könnte dies dem Nutzer Zeit und Unterbrechungen sparen, die andernfalls nötig wären um dieselbe Information direkt zu erfragen (z.B. Informationen zur Nutzeridentität, Handhaltung sowie weiterem Kontext). Verhaltenssensitive Nutzerschnittstellen können solche Informationen auf verschiedene Arten nutzen, insbesondere um sich an unterschiedliche Nutzer und Kontexte anzupassen. Wichtige Forschungsfragen adressieren deshalb das Verständnis von Verhaltenscharakteristika und -einflüssen, deren Modellierung, sowie Konzepte zu Inferenz und Reaktion und deren Integration in die Nutzerschnittstellen. Diese Fragen werden im Rahmen dieser Dissertation in mehreren Studien untersucht. Dazu werden sowohl grundlegende Verhaltensaspekte von Interaktionen mit Touchscreens auf mobilen Geräten analysiert, als auch eine Reihe von konkreten Anwendungen mittels nutzbarer Prototypen betrachtet. Dabei werden drei Anwendungsbereiche und -ziele untersucht:

1) *Verbesserung der Eingabeleistung*, durch Modellierung des invidividuellen Zielverhaltens eines Nutzers bei der Verwendung des Touchscreens, um zukünftige Eingaben zu korrigieren und somit die Eingabegenauigkeit zu verbessern. Hierbei zeigen sich Herausforderungen und Möglichkeiten bei der Nutzung von Verhaltensvariabilitäten, die sich aus mehreren Faktoren ergeben, darunter: Position, Größe und Form des Zielelements auf dem Touchscreen, verwendete Hand und Finger bzw. Daumen, Nutzung eines Stifts, Bewegung während der Eingabe, sowie Größe des Geräts. Die Ergebnisse geben darüber hinaus Hinweise zur Modellierung und Inferenz basierend auf Daten zum Zielverhalten und führen zu konkreten Ansätzen für die Simulation von Nutzerverhalten sowie der Erkennung von Verhaltensänderungen.

2) *Förderung von Privatsphäre und Sicherheit*, durch die Analyse von Mustern im Ziel- und Tippverhalten, womit Nutzer implizit während der Eingabe identifiziert bzw. unterschieden werden können. Hierbei betrachtet die vorliegende Arbeit auch spezifische Herausforderungen bei mobilen Geräten, insbesondere wechselnde Handhaltungen bei der Nutzung. Zentral wird zudem der biometrische Wert von jenen Verhaltensmerkmalen herausgestellt, die sich aus der Analyse des Zielverhaltens ergeben. Der Nutzen dieser Merkmale wird sowohl im Labor als auch bei Interaktionen im Alltag untersucht. Auf methodischer Ebene werden die Auswirkungen häufig getroffener Annahmen bei der Analyse solcher Daten und Systeme quantifiziert und diskutiert.

3) *Verbesserung der Ausdrucksstärke* von Interaktionen, durch das Verknüpfen von Verhaltensmerkmalen in der Eingabe mit Eigenschaften der Ausgabe. Insbesondere wird eine Tastatur vorgestellt

und evaluiert, welche die Textdarstellung dynamisch verändert, in Abhängigkeit des aktuellen Tippverhaltens. Die Ergebnisse zeigen, dass Nutzer grundlegende Kontexte sowie individuelle Personen anhand dieser Schriftanpassungen unterscheiden können. Außerdem werden die Schrifteinlüsse von den Nutzern für persönliche Kommunikation mit kreativen Effekten verwendet.

Darüber hinaus stellt diese Dissertation mehrere Konzepte und implementierte Werkzeuge vor für das Sammeln von Verhaltensdaten aus der Interaktion, der Analyse und Modellierung von Interaktionsverhalten, sowie dem Erstellen von verhaltenssensitiven und adaptiven Nutzerschnittstellen für mobile Geräte mit Touchscreen. Diese Beiträge unterstützen Forscher und Entwickler bei der Untersuchung und praktischen Umsetzung von solchen Nutzerschnittstellen.

Insgesamt zeigt die vorliegende Arbeit, wie Verhaltensmerkmale in der Interaktion mit mobilen Geräten mit Touchscreen zum Vorteil der Nutzer adressiert und genutzt werden können. Vor diesem Hintergrund werden außerdem Transfer und Wiederverwendung von Verhaltensinformationen und -modellen diskutiert, zum Beispiel im Hinblick auf Kompromisse zwischen Bedienbarkeit und Privatsphäre bzw. Sicherheit. Schließlich reflektiert die Arbeit die generelle Rolle verhaltenssensitiver Nutzerschnitstellen. Dabei zeichnet sie eine Perspektive, in der solche Nutzerschnitstellen der direkten Einbettung von “Erwartungen” an das Bedienverhalten in interaktive Systeme dienen.

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Journeys are the midwives of thought.
– Alain de Botton, The Art of Travel, 2002

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Collaboration Statement

The projects that build up this thesis would not have been possible without the excellent support of my supervisors, colleagues and students. In appreciation, I thus use the scientific *"We"* throughout the main body of this thesis.

Here, I clarify my personal contribution. In favour of the formal clarity of this "disclaimer", I decided against thanking individual people in this section. You deserve a dedicated section for that.

Contribution of colleagues: The following statements relate to those publications in which the respective person appears as a co-author. The research was conducted in close cooperation with my supervisor Florian Alt, who provided feedback on all aspects of the work. My colleague Alexander De Luca provided feedback on concepts, study designs, and the manuscripts. During my stay at the University of Glasgow, all work was conducted in close cooperation with my supervisors Roderick Murray-Smith and Simon Rogers, who provided feedback on all aspects of the work.

Contribution of students: Students contributed via Bachelor and Master theses projects, as well as other practical research projects. I was the main supervisor and provided the research topics, ideas and goals. All projects were conducted in close cooperation with weekly meetings. I was the key decision maker throughout all steps (e.g. regarding concepts, prototype features, study designs, evaluations).

Content and presentation: I developed all core ideas and concepts, supported by feedback, discussions, and suggestions from my supervisors, colleagues and students. I implemented all analyses scripts, prototypes, and software contributions. Exceptions are listed in Table 1. I wrote the complete text for all publications (see *Contributing Publications*), computed all data analyses which appear therein, and created all figures and tables. My co-authors contributed feedback on the manuscripts. I personally revised all papers, integrating this feedback.

Table 1 clarifies further contributions of others to individual projects and publications.

Project / Publication	**Contributions of Others**
Buschek et al. [P10]	Roderick Murray-Smith provided the research topic of investigating offset models across devices.
Buschek et al. [P9]	My student Julia Kinshofer implemented the Android study app and conducted the study.
Buschek et al. [P5]	My student Benjamin Bisinger implemented the *ResearchIME* Android app and its backend, and conducted the online survey and study. I reused parts of the Python code from his data processing and analyses scripts for computing the evaluations in the paper. Beyond this paper, my students Florian Thoma and Timo Erdelt further developed the *ResearchIME* Android app and backend.
Buschek [P1]	The project uses the data collected by my student Benjamin Bisinger (see above).

Table 1: Clarification of contributions in specific projects and publications.

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1 Introduction

It is widely believed that "everyone should be computer literate". [...]
The premise of the research that is reported in this volume is that
"computers should be user literate".

Browne, Totterdell & Norman, Adaptive User Interfaces, 1990

1.1 Thesis Statement

Mobile touch devices have become ubiquitous tools in our everyday lives. We use them, for example, to communicate, to navigate information spaces and physical space, and to capture, store and access personal data, such as photos. Thus, they often become personal devices, linked to an individual and the digital part of their world. A common window and door to this world is the touchscreen. Both from this personal use and the importance of the touch interface arises the main assertion of this thesis: Mobile touch interaction can be improved by enabling touch interfaces to assess and consider *how* the user executes these interactions.

Our work supports this assertion with an exploration of three application areas for behaviour-aware mobile touch interfaces. We first give concrete examples from these areas (see Figure 1.1): For instance, behaviour-aware user interfaces can learn about touch behaviour and errors of a particular user, in order to correct that person's future touches to render the touchscreen more accurate (Figure 1.1a). Related, behaviour-aware interfaces may also use expectations about touch behaviour to better understand the user's intention. For example, such interfaces could then interpret input more reliably, despite inaccuracy (e.g. due to mobile use – touching while moving). This approach has been employed successfully by mobile touch keyboards to enable fast and accurate typing (see e.g. [56, 170]). With our *ProbUI* concept and framework [P3], our research contributes to integrating expectations about touch behaviour into more general touch interfaces (and their development). For instance, we used *ProbUI* to realise sliders, lists, and menu widgets which adapt their shape and layout to the currently used hand posture (Figure 1.1b and c). Another example addresses usable privacy and security: Identifying or (re)authenticating users based on their touch behaviour characteristics might allow users to avoid (some) explicit interactions for identity management (e.g. switching accounts, "logging in"). Finally, our behaviour-aware keyboard and chat app *TapScript* personalises the user's font for mobile text messaging based on input behaviour details, like finger placement or (device) movement (Figure 1.1d).

In summary, our work explores the following three aspects in which behaviour-aware touch interfaces improve our personal mobile devices and interactions:

Enhancing input capabilities: In multiple user studies, we investigate touch targeting errors, that is, users' offsets between intended targets and sensed touch locations. We evaluate in detail how offset patterns and models are influenced by device, hand posture, implement, mobility, and GUI target size and shape at different screen locations. We show and discuss improvements of touch accuracy with these models, as well as related challenges. Our work also informs modelling and inference based on such data, and presents and evaluates models for simulating touch targeting behaviour and detecting behaviour changes.

Facilitating privacy and security: Our user studies of targeting and typing behaviour show that touch offsets and other touch features have biometric value for (implicit, continuous) user identification and authentication. We show that this provides opportunities to improve usable privacy and security systems on mobile touch devices, contributing to the protection of users' data. We also reveal and address mobile-specific challenges, in particular changing hand postures. More generally, we assess and discuss the influence of common evaluation assumptions in this area as well.

Increasing expressiveness: We propose to embrace variability in individual touch input behaviour as additional degrees of freedom to influence output. We demonstrate this idea with our mobile keyboard and chat app *TapScript*, which dynamically modifies the font based on input behaviour while typing. Our studies show that users can distinguish basic contexts and individuals. They perceive communication as more personal and explicitly control font influences for creative effects.

Beyond investigating these application areas, this thesis contributes several concepts and implemented tools for collecting behaviour data, analysing and modelling touch behaviour, and creating behaviour-aware and adaptive mobile touch UIs. Together, these contributions support researchers and developers in investigating and building behaviour-aware mobile touch UIs.

Our research overall shows how variability in mobile touch behaviour can be addressed and exploited to support users by contributing to effective, secure, and personalised mobile interactions and systems. Looking ahead, we discuss opportunities for transfer and reuse of touch behaviour models and information across applications and devices. As a particular case, we outline how this reframes and affects tradeoffs of privacy/security versus usability. Finally, we further reflect on the general role of behaviour-aware interfaces in Human-Computer-Interaction. We outline a general perspective that regards such interfaces as a way of embedding expectations about user input into interactive artefacts.

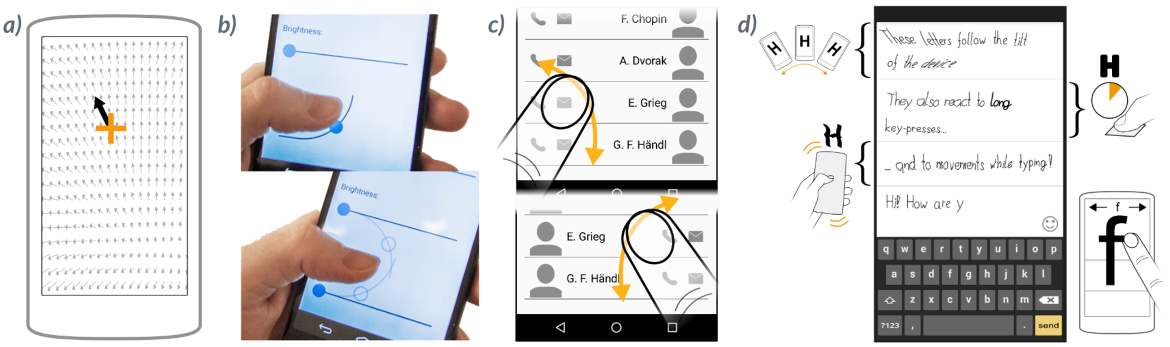

Figure 1.1: Examples for behaviour-awareness in mobile touch UIs from our research: *a)* Using a touch targeting model (visualised as arrows) to correct a user's touch location to improve accuracy; *b)* these *ProbUI* sliders adapt their shape to match the thumb's movement arc (top), including feedback about uncertainty (bottom, uncertain slider selection); *c)* this *ProbUI* contact list flips its button/name alignments depending on the finger trajectory, thus adapting to left vs right hand use; *d)* the *TapScript* keyboard and chat app personalise fonts based on several aspects related to input behaviour.

1.2 Contributing Publications

A note on the format and relationship of this document and the publications: This is a cumulative dissertation. The individual research projects have been published before. This additional thesis document presents a summary and overarching discussion, relating the work to the literature. Thus, it serves the roles of intro, related work and discussion sections – introducing and reflecting on the content of the published papers. These publications are listed in their own reference list below. Citations of the contributing publications are marked by "P" (e.g. [P1]). The full publications are available at the given DOIs below. The overarching narrative and concept of *behaviour awareness* emerged from this research and reflection. Thus, the term is introduced here and does not appear directly in the earlier publications.

[P1] Daniel Buschek. "A Model for Detecting and Locating Behaviour Changes in Mobile Touch Targeting Sequences". In: *Proceedings of the 23rd International Conference on Intelligent User Interfaces*. IUI '18. ACM, 2018. DOI: 10.1145/3172944.3172952 (cited on pp. xi, 3, 5, 7, 8, 11–14, 19–21, 23, 25, 28, 34).

[P2] Daniel Buschek. "There is more to biometrics than user identification: Making mobile interactions personal, secure and representative". In: *it - Information Technology* 58.5 (2016), pp. 247–253. DOI: 10.1515/itit-2016-0013 (cited on pp. 5, 12, 14, 15, 24, 28, 33, 37).

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[P3] and [P8] received *Honourable Mention Awards* at the respective conferences.

1.3 Overview and Guiding Research Questions

As a first overview of our work, Table 1.1 provides a summary structured by six main areas and questions. These motivated and guided the research contributing to this thesis.

Empirical	Conceptual	Constructive
RQ1 - Analysis: How do users execute basic mobile touch interactions? Which factors influence this behaviour?		
Analyses of targeting behaviour on smartphones, with factors and effects: hand and finger [P4, P6, P10]; target location, shape and size [P4, P6]; implement and mobility [P9]; device-specific [P10] and user-specific [P6] differences.	Revealing connections between these aspects, in particular influence of GUI and hand posture on user individuality of touch behaviour [P6, P7].	*ResearchIME* keyboard app for observing users' "natural" mobile typing behaviour in the wild [P5].
RQ2 - Modelling: How can we model relevant aspects of users' mobile touch behaviour?		
Investigation of the above factors and effects for touch targeting (offset) models [P4, P6, P9, P10]. Evaluation of different models for capturing user-specific typing behaviour [P5, P7].	Concept for transfer of offset models across devices [P10]. Generalising GUI target representations to prob. gestures ("bounding behaviours") [P3]. Offset model that handles touch targeting sequences [P1].	*TouchML* toolkit that implements offset models for research and applications [P4]. *ProbUI* framework which implements the "bounding behaviours" models [P3].
RQ3 - Inference: Which information can interfaces infer from mobile touch behaviour? How?		
Evaluation of inferring user [P6, P10], user changes [P1], hand/finger [P4, P10] and implement [P9] based on touch targeting behaviour with offset models. Evaluation of inferring user from typing behaviour with various models [P5, P7].	Concept for inference with offset models [P1, P4, P6, P10]. Concept for inferring user from password typing with changing postures [P7]. *ProbUI* concept for inferring intended gesture and target from touch behaviour [P3].	Implemented offset-based inference examples in *TouchML* [P4]. Implemented *ProbUI* framework; example widgets which infer left vs right hand use [P3].
RQ4 - Application: How and in which application areas can users benefit from behaviour-aware mobile touch interfaces?		
Studies on: 1) Improving touch accuracy with offset models [P4, P6, P9, P10]. 2) Identifying & authenticating users based on touch behaviour [P1, P6, P7]. 3) Facilitating personal messaging by adapting fonts based on input behaviour [P8].	Overarching motivation and discussion of application areas for behavioural (biometric) information beyond security [P2]. GUI target representation concept for facilitating UI adaptations in *ProbUI* [P3]. A concept that links input behaviour to font adaptations [P8].	Prototypes: 1) Improving touch accuracy in apps and on websites [P4]. 2) *TapScript* chat & keyboard app for dynamic font personalisation [P8]. 3) *ProbUI* widgets which react to left vs right hand use [P3].
RQ5 - Evaluation: How can we evaluate behaviour-aware mobile touch interfaces and their components?		
Measuring influences of evaluation assumptions on accuracy for touch biometrics with password typing data [P7]. Experiences from lab and field studies and online surveys, with users and developers.	Concept for estimating biometric value of mobile touch GUIs [P6]. Critical discussion of evaluation assumptions in touch biometrics [P7].	Visualisation and evaluation methods for touch targeting behaviour and models in the *TouchML* toolkit [P4]. Live model visualisations for debugging in *ProbUI* [P3].
RQ6 - Engineering: How can we facilitate the development and implementation of behaviour-aware mobile touch interfaces?		
Insights and feedback from: 1) Developers learning *ProbUI*'s declarative language *PML* with a tutorial and 2) using *ProbUI* in a workshop [P3]. Experiences from implementing prototypes.	*ProbUI* framework; with declarative language *PML* for specifying expected touch behaviours (gestures) in GUIs; concept for automatically inferring probabilistic models from *PML* statements [P3].	Implementation of *ProbUI*, with *PML* and its mapping to probabilistic models [P3]. *TouchML* toolkit that implements offset models for research and applications [P4].

Table 1.1: Overview of our work organised by research question and contribution type, following Laudan's taxonomy [94], as adapted for HCI by Oulasvirta and Hornbæk [123].

1.4 Research Approach and Methods

Research Approach and Perspective

To set the stage for more specific discussions later on, here we first characterise and reflect on our research with respect to broader structures and perspectives.

Themes and Structure The research contributing to this thesis is structured into three larger themes: First, we *analyse and model* mobile touch targeting behaviour to assess variability and consistency and the influence of several factors. Second, we explore three *application areas* in which users could benefit from these models and related behaviour information. Third, we investigate and implement *methods and tools* to facilitate building touch behaviour models and behaviour-aware mobile touch interfaces. Roughly, these three themes also can be seen as subsequent steps in our overall research process. However, the work was often intertwined and inspired across them (e.g. generalising tools based on experiences with prototype implementations and data analyses from other studies).

The Three Paradigms of HCI Harrison et al. [62] distinguish three paradigms of HCI. Besides focus and values, these also differ in their "ways of knowing" along several dimensions. Considering those, we characterise our own methodological stance as follows: In the tradition of the Second Paradigm, we seek to contribute *objective* and *generalised* knowledge related to interaction behaviour and influencing factors, and accordingly value methods that support this (e.g. controlled experiments, statistical data analyses). In the same vein, our framing of behaviour-aware UIs highlights and values *information* about behaviour which is assessed and utilised by such UIs, for example with statistical models. However, we also value opportunities of behaviour awareness in UIs to enable interactions that stimulate *human interpretation* – a Third Paradigm value [62]. Our work on *TapScript* [P8] uses this perspective, emphasising interest in a more experiential quality of typing behaviour over Second Paradigm performance measures.

Interaction and Practice Paradigms Our behaviour-aware UIs focus on awareness of *input* behaviour, and thus on UI and interaction tasks. This follows what Kuutti and Bannon [93] called "Interaction Paradigm" (as contrasted with the "Practice Paradigm"). Our analyses of targeting behaviour present a prime example: Interaction is at the centre, influenced by context. However, we also argue that practical value of behaviour-aware UIs arises from their capability to utilise and/or account for behaviour *variations*. These are often due to (changing) context factors. Thus, our view includes aspects of Kuutti and Bannon's "turn to practice", towards "the ultimate context" – artefacts in real everyday use in the wild. More specifically, such aspects are present in 1) our work on behaviour-aware UIs for "expressiveness", in particular regarding users' daily mobile messaging (*TapScript* [P8]), and 2) our *ResearchIME* [P5] concept and tool, which facilitate studies of free typing in the wild. Overall, we thus position our work in the tradition of the primary interaction focus, yet also value context not only as an influence but as an integral interest of many behaviour-aware UIs. Besides controlled lab studies, our research thus seeks to facilitate the use of methods which capture changing contexts in the wild, both for behaviour analyses and data collection as well as prototype deployments. Still, this is done with a focus arising from the Second Paradigm and Interaction Paradigm (e.g. *ResearchIME* facilitates collecting *quantitative* usage data, not e.g. users' surrounding social experiences).

Perspectives on Interaction Besides HCI paradigms, our research perspective can be characterised via its view of interaction. Hornbæk and Oulasvirta provide a recent overview and discussion of seven such views [74]. Two seem particularly relevant to our work: First, interaction can be conceived as *transmission of information*. This prespective underlies our work on touch targeting: Touch offset models increase targeting accuracy and thus reduce the noise (i.e. varying touch points) associated with messages along a channel (i.e. intended target selections). To argue that this improves the UI thus follows the perspective that good interaction is about achieving high throughput. Moreover, this information view is also present in our work on touch biometrics, in particular with regard to measuring individuality of user input behaviour and estimating "biometric value" of touch GUIs [P6]. Our general framing of behaviour-aware UIs in this thesis also follows this perspective. For example, we outline that such UIs assess and consider input behaviour *information* (see Section 2.1). Second, interaction can be seen as *control* [74]: Users are controllers who continuously act based on feedback about the system's state. This view is fundamental to the concepts and goals of our *ProbUI* framework [P3], which accommodates continuous touch interaction with live feedback and faciliates UI adaptations. Moreover, some of the questions highlighted in Section 3.2 arise from this control view.

Empirical Research Methods

We employed a variety of empirical methods and tools. Table 1.2 provides an overview of studies and datasets. The following paragraphs motivate and reflect on these choices.

Lab studies were used to investigate mobile touch behaviour under controlled conditions. This allowed us to isolate and analyse the influence of individual factors, such as target location [P4, P6, P9, P10], target shape and size [P4, P6], hand posture [P4, P6, P7, P10], as well as implement and mobility [P9]. Moreover, lab studies allowed us to *repeatedly* study behaviour under the same conditions to observe consistency and change in people's mobile touch behaviour over time [P4, P6, P7, P9].

Field studies helped us to explore how people behave and use prototypes in daily live: *TapScript* [P8] personalised text message fonts based on typing behaviour. A field study allowed us 1) to observe real behavioural variability, and 2) to assess users' experiences with our concept embedded into actual personal communication. Moreover, we collected typing behaviour "in the wild" via a modified Android keyboard app [P1, P5]. This allowed us 1) to study everyday typing behaviour, keyboard usage, and biometrics [P5], and 2) to evaluate our sequential offset model for detecting behaviour changes on real-world touch sequences [P1].

A *workshop* was set up as a special type of lab study to evaluate the use of our *ProbUI* framework [P3] for creating behaviour-aware touch GUIs. This allowed us to directly observe how developers approach and use our framework upon first contact.

Interviews were conducted to gain qualitative insights into experiences with using our prototypes. We used group interviews to assess how users' chatting behaviour and experiences were influenced by our font personalisations in *TapScript* [P8]. Moreover, interviews provided feedback and reflections by developers after using our *ProbUI* framework [P3].

The *think-aloud* technique was used to gain insights into people's assumptions, reasoning, and "pain points". We used this during the workshop evaluation of *ProbUI* [P3].

Name	Summary	Type	N	Refs.
TAPS-I	Participants targeted cross-hairs with the right thumb on multiple smartphones in portrait orientation; partly also with the left thumb, and in two sessions.	lab study	30	[P10]
TAPS-II	Participants targeted cross-hairs, buttons shaped like keys and app-icons, and full width buttons with the right thumb and index finger on a smartphone in portrait orientation in two sessions.	lab study	24	[P1, P4, P6]
TAPS-STYLUS	Participants targeted cross-hairs with two kinds of styli and the right index finger on a smartphone in portrait orientation while sitting and walking in two sessions.	lab study	28	[P9]
PWD-TYPING	Participants entered six given passwords 20 times each, using the right thumb, both thumbs, and the right index finger on a smartphone in portrait orientation in two sessions.	lab study	28	[P7]
TYPING-WILD	A modified keyboard app collected typing touches from participants' free text entry on their own devices used "in the wild" for three weeks.	field study	30	[P1, P5]
TYPING-WILD-SURVEY	Participants rated perceived privacy violation of different filtering concepts for privacy-respectful collection of free typing data in the wild.	web survey	349	[P1]
TAPSCRIPT-CHAT	Groups of participants used our chat app with *TapScript* keyboard and fonts for one to three weeks on their own smartphones.	field study	11	[P8]
TAPSCRIPT-SURVEY	Participants distinguished typists and walking/sitting contexts by looking at messages rendered in *TapScript* fonts created by five users in a pre-study.	web survey	91	[P8]
PROBUI-DEV	Android developers were introduced to *ProbUI* in a 20 minute presentation and completed six coding projects with it while "thinking aloud".	workshop	8	[P3]
PROBUI-SURVEY	Participants read a tutorial on *ProbUI*'s modelling language PML, then completed three kinds of tasks: matching gestures to PML and PML to gestures, and writing PML themselves.	web survey	33	[P3]

Table 1.2: Overview of empirical research contributing to this thesis.

Questionnaires supported all studies. Beyond demographics and specific questions of interest, we used them to assess user perception of the tasks, including controlled factors. This allowed us to compare measured and subjective results (e.g. see [P5, P9]).

The experience sampling method (ESM) was used to enrich logging data. In particular, we assessed hand postures via ESM in our typing study in the wild [P5]. This enabled comparisons of free typing behaviour between postures and revealed further insights. For example, we found that users underestimated their use of typing with both thumbs in our pre-study questionnaire compared to assessments in situ via ESM.

Web surveys were used to reach a larger number of people and to address a specific audience. In particular, we deployed a web survey to gain insights into the overall perception of personalised fonts in *TapScript* [P8] by an extended number of people. Another web survey was created to reach seasoned Android developers via a corresponding online forum to gather feedback and assess the basic usability of the declarative touch gesture language "PML" designed for our *ProbUI* framework [P3].

Limitations of these methodological choices are discussed in the respective parts and in Section 3.4.

Methodological Reflections and Contributions

Here, we highlight particular aspects which contribute to methodology and related practices in this research context, also beyond our own work.

Combining and comparing lab and field results: As a general reflection across multiple projects, we consider results obtained in different environments. In particular, we studied typing biometrics both in the lab [P7] and in the wild [P5]. In both studies we found that spatial touch features outperformed temporal ones for user identification/authentication. This combination seems generally suitable for work on behaviour-aware UIs, since it covers different aspects of behavioural variability: In the lab we study variability between specific (controlled) factor levels, which the UI might want to consider and/or address. In contrast, field studies capture real-life variability and occurrence of these factor levels, as well as behaviour variability "as noise", which is relevant with regard to robustness of the behaviour-aware system.

Quantifying influences of evaluation assumptions for touch biometrics: We examined the influence of several evaluation assumptions for mobile touch typing and targeting biometrics [P6, P7]. Our experiments show that one obtains overly optimistic results by 1) using data from a single day, or 2) assuming that the system knows other users or even the particular attacker, or 3) assuming fixed hand postures. We quantify these influences by comparing results obtained under different assumptions (e.g. changes in user authentication error rates). Our results and discussion emphasise that evaluation schemes for touch biometrics analyses need to be carefully considered with respect to their implied assumptions about deployments in practice. For example, evaluations with data from only one hand posture imply the (often unrealistic) assumption that users always interact with the same posture.

Logging "natural" touch typing behaviour beyond the lab: We proposed and studied different filters for privacy-respectful logging of free text entry behaviour [P5]. We found that randomly logging short *n*-grams yields useful data for many research interests, yet filter parameters need careful consideration. Moreover, we contribute a keyboard app and backend which implement this concept to facilitate studies of touch typing behaviour, keyboard use, and related biometrics in the wild. Section 3.3.1 discusses more details.

Direct integration of ESM into touch GUIs: As part of *ResearchIME* [P5], we integrated an ESM [32] screen directly into the keyboard GUI to assess users' typing hand postures. This stands in contrast to, for example, presenting ESM via separate notifications and apps (cf. survey by Berkel et al. [11]). Our ESM view showed up as a keyboard overlay when opening the keyboard. From participant feedback and quantitative data, we learned that this yields many answers, since it cannot be overlooked. Moreover, it introduces no extra loading time beyond the existing keyboard slide-in animation. ESM interaction also takes place at the same screen location as the main task, facilitating a fluid transition from answering to typing. Pretests and feedback showed that this integrated ESM view should stay limited to a single action (tap) and an easy-to-process presentation (we used pictograms). Moreover, it should not be shown too frequently to avoid annoyance. Such direct integration might be useful for other studies as well (e.g. context-aware messaging). The specific ESM content in our keyboard app could be modified to assess other data than hand postures (e.g. mood). Future work might investigate further aspects, for example, comparing blocking and non-blocking integration of ESM screens.

2
Background and Definitions

This section provides background information and definitions of central terms used throughout this thesis. It further discusses their relationship to other terms and concepts.

2.1 Touch Behaviour Information

We define *touch behaviour* as behaviour exhibited by users to perform interactions that involve a touchscreen. For mobile touch devices in particular, concrete examples include tapping on buttons, typing on a keyboard, moving a slider, pinching with two fingers to zoom on a map, and so on.

Following the way that Dey and Abowd formulated their definition of context information [39], we define *touch behaviour information* as any information that can be used to characterise how a touch interaction is performed. Examples include the speed of a finger gliding on the screen, touch pressure, duration of interaction, and the rhythm of tapping and typing in interaction sequences.

The term *information* instead of, say, *data* or *features*, is used to respect results derived from the "raw" data via processing, modelling, and inference. This includes, for example, derived information about the hand or finger in use [P4, P10], or the interacting user [P7, P6].

The examples given above already hint at a focus: This thesis focuses on touch behaviour information related to the *physical* execution of touch interactions. In a larger view, touch behaviour could be linked to higher-level aspects, for example, daily patterns of smartphone use or decision-making processes. Such aspects are not considered here.

2.2 Assessing Touch Behaviour Information

Touch behaviour information is obtained by observing a user's touch behaviour in interactions. In general, such observations could be qualitative – e.g. with a human reporting on what they notice about the behaviour – or they could be quantitative, which is the main approach taken in this work. Hence, "observation" here always involves data recording and quantitative analyses of said data. These analyses are structured into three parts.

Measurement: Some touch behaviour information can be measured directly from typical interaction logs, such as task completion time. Direct measurement involves minimal processing and no additional assumptions beyond the data.

Modelling: Models help to capture and reveal underlying patterns not directly observable in the raw data. These patterns may depend on other properties of the user, the user interface, and the context of use. The work contributing to this thesis models 2D targeting error (offset) patterns across the screen [P1, P4, P6, P9, P10], as well as touch gestures in mobile GUIs [P3]. We could also say that such models represent our "expectations" about future behaviour.

Inference: Finally, quantitative data analyses may aim to infer information, often involving previously obtained models. This information can be regarded as implicit (cf. [P2]) and often tells us something about the user and context of the observed touch interaction. For example, we infer user identity (and user changes) as well as hand in use from touch targeting behaviour [P1, P4, P6, P10] and from typing behaviour [P5, P7]. We also propose and implement GUI elements that infer finger and hand in use from touch interactions with sliders, menus, and lists [P3].

2.3 Behaviour Awareness as a Property of UIs

We define *behaviour awareness* as a property of user interfaces as follows: A behaviour-aware user interface assesses information about interaction behaviour to take into account *how* the user executes interactions with it. This is a general definition; in our case, we assess and take into account touch behaviour information, including measurement of touch input features, modelling of related patterns, and consequently inference and adaptation.

Note that our definition does not *require* interfaces to adapt to behaviour information, as this would be too limiting. For example, an interface that simply displays behaviour information would not be behaviour-aware if adaptation was required. A similar line of thought underlies the omission of adaptation in the definition of context-aware systems by Dey and Abowd [39].

Nevertheless, we envision that most behaviour-aware UIs respond to behaviour information by adapting interface and/or resulting output. They may do so during an ongoing interaction and/or with regard to future use. The details of this response are not prescribed by definition, yet this thesis explores examples in three application areas (see Section 3.2).

This awareness is not to be confused with other uses of the term in HCI. For example, groupware and awareness systems [42, 75] aim to make one user or group aware of another's activity, context, and so on. Moreover, ambient displays make people aware of information such as weather or stock values [166]. This is awareness between multiple people or between a person and surrounding information. In contrast, we describe a relationship between a user and an interface, which is aware of the interacting user's details of interaction behaviour.

Finally, "awareness" here is not meant to convey something akin to human consciousness, but merely "using information about", in the sense in which it is also understood for context-aware systems [39].

2.4 Discussion of Related Concepts

One might ask how behaviour-aware user interfaces as described in this thesis relate to other concepts, such as context awareness or intelligent and adaptive user interfaces. Table 2.1 gives an overview of several related concept classes/definitions and main connections and distinctions. These concepts were selected based on insightful and reoccurring discussions over the course of this thesis research; the goal here is to characterise the work and embed it into conceptual context. However, we do not claim that this is a comprehensive list.

Concept	Common Ground / Connection	Focus / Extension / Difference
Context Awareness	Behaviour information can be seen as a subset of context information.	Behaviour-aware UIs 1) provide a source of behaviour information (e.g. for other context-aware systems), and 2) use it themselves (e.g. to adapt).
Intelligent UIs	Behaviour awareness contributes to "intelligence" in UIs.	In particular: behaviour-aware UIs embed expectations about input behaviour.
Adaptive UIs	Behaviour-aware UIs can be adaptive.	In particular: adaptation is based on input behaviour information.
Behavioural Biometrics	Shared interest in utilising variability and individuality of human behaviour.	Extended application scope: not limited to security/privacy.
Tools vs Agents	Behaviour-aware UIs as interfaces to tools, not agents.	Awareness of input behaviour, i.e. not replacing user action.
Fore-/Background	Varying degrees of user attention and intention; using background "signals" to support foreground interaction.	"Background in the foreground": behaviour-aware UIs utilise ("unintentional") behaviour details exhibited in intentional interactions.

Table 2.1: Overview of related concepts with connections and comparisons to the described concept of behaviour awareness for (mobile touch) user interfaces.

Behaviour Awareness & Context Awareness

Regarding context awareness, we argue that behaviour information is a subset of context, if we view the way a user executes an interaction as part of that interaction's context. Beyond that, behaviour-aware UIs can be seen as a source of information that facilitates context awareness. As an example, touch targeting behaviour reveals hand posture [P4, P10], which is often regarded as important context information (see e.g. [54, 55, 68]). Hence, a behaviour-aware user interface that infers hand posture from touch behaviour – for example to adapt the GUI as in our *ProbUI* framework [P3] – would also be context aware. On the other hand, not all context-aware systems are behaviour-aware: For example, the considered context information might simply not be part of the user's interaction behaviour (e.g. weather).

Behaviour-Aware UIs & Intelligent User Interfaces

We regard behaviour awareness as a way of contributing to "intelligence" in UIs. In particular, it sets a focus on (predictive) processing of behaviour signals along those channels directly employed by users for interaction, in our case mobile touchscreen interactions. In other words, behaviour awareness embeds expectations about user behaviour into the UI itself (see Section 4.1). Since building and utilising adequate expectations demands information and models about the world [30], we argue that such user interfaces may then be deemed more "intelligent" than non-behaviour-aware ones. For example, our work on offset models [P1, P4, P6, P9, P10] captures expectations about future targeting behaviour to improve touch accuracy. Moreover, widgets in our *ProbUI* framework [P3] expect – and adapt to – more than one way of being used (e.g. slider bends to match thumb reach in left-handed vs right-handed use).

Behaviour-Aware UIs & Adaptive User Interfaces

Behaviour-aware user interfaces can be adaptive as well if they adapt to behaviour instead of just assessing and/or displaying it. They then represent a subset of adaptive interfaces, namely those that base their adaptations on (input) behaviour information, as defined in this thesis. Moreover, this subset overall favours implicit adaptations (e.g. see *ProbUI*'s adaptive widgets [P3]), as opposed to explicit user decisions (cf. adaptive vs adaptable UIs [19]; "levels of adaptation", e.g. [95]). The latter are not excluded per se, though, and one might explore behaviour-aware interfaces that present the user with adaptation options (cf. "adaptation tips" [120]), in our case based on behaviour information.

Behaviour Awareness & Behavioural Biometrics

We see a strong link between behaviour awareness and behavioural biometrics. Fundamentally, both concepts build on variability in human behaviour. They particularly share a common interest in detailed behaviour information related to the execution of certain physical tasks, such as in our case operating a mobile touchscreen device.

The main distinction between the concepts lies in their target applications for such behaviour information: The term "biometrics" is traditionally strongly associated with the distinction and recognition of individual human beings ("identity management", see e.g. [80]). In contrast, behaviour-aware user interfaces as envisioned in this thesis also utilise behaviour information beyond this. We also covered the security aspect in our work on distinguishing users based on password typing [P7] and targeting behaviour [P1, P6]. However, we further used behavioural (biometric) information to adapt and personalise both input method (offset models adapt touch interpretation [P4, P9, P10]) and the interaction's output (dynamic font adaptation in *TapScript* [P8]). An essay by the author [P2] presents a more detailed motivation and discussion for opening "biometrics" to encompass more than security in this way (also see Section 3.2).

Behaviour-Aware UIs & Tools vs Agents

An ongoing discussion in HCI research is concerned with the degrees of autonomy and integration in the human-computer relationship (see e.g. discussions spanning conferences from CHI '97 [145] to CHI '17 [46]). In this regard, all our thesis projects view behaviour-aware UIs as interfaces to tools. These might be deemed intelligent tools, but we do not cast them as intelligent agents. Metaphorically speaking, the hammer assesses grasp and swing in order to adapt to it, yet it must still be wielded in the first place (cf. instrumental interaction [7] vs dialogue with agents or servants).

This is evident in our focus on channels directly employed by users for using those tools, thus in our case touchscreen interaction. In other words, in this thesis, behaviour-aware user interfaces focus on awareness of *input* behaviour. In contrast, cast as an agent, we might instead aim to extend that agent's awareness through perception along any suitable channel, employed directly for interaction or not. Moreover, an agent might aim to replace (the need for some) explicit user actions (e.g. by acting on the user's behalf), while our behaviour-aware UIs aim to "get more out of" the user's actions.

Behaviour-Aware UIs & Foreground/Background Model

Finally, it is particularly interesting to relate behaviour awareness to the foreground/background model described by Buxton [23], as adapted and discussed for sensor-enhanced mobile devices by

Hinckley et al. [69]: *Foreground interaction* describes intentional “step-by-step human guidance for the computer” [69] (e.g. typing). In contrast, *background sensing* registers actions that users “would have had to perform anyway” [69] as part of their task (e.g. picking up the phone). Most importantly for our work, such background sensing can also facilitate foreground interaction (e.g. directly launching the messenger when picking up the phone after receiving a text).

Hinckley et al. [69] particularly refine the foreground/background model to view it as degrees of attention and intention (foreground: intentional; background: unintentional). Our concept of behaviour-awareness in user interfaces covers this spectrum by utilising behaviour information as defined above: These “details” of (input) behaviour are observed for intentional interactions (i.e. foreground), yet they are usually not intentionally controlled (i.e. in the background). For example, offset patterns result from a variety of factors (as our work shows [P4, P6, P9, P10]), but usually not from a user’s intention to, say, touch too far to the right of a target. The user’s decisions might still influence the pattern, for example, by choosing a certain hand posture – although it is unlikely that the change of the pattern was the primary goal of that decision (rather, hand posture is chosen e.g. due to encumbrance). However, users may start to control previously unintentional behaviour details once a behaviour-aware UI introduces a feedback loop (e.g. see our work on *TapScript* [P8] and the discussion in Section 3.2.2).

Thus, related to the foreground/background view, it is 1) the consideration of “interaction signals” with varying degrees of attention and intention, and 2) the idea of combining background sensing and foreground interaction that is also at the heart of our work. Hence, to summarise, behaviour-aware user interfaces as envisioned in this thesis utilise the “background in the foreground”.

As an alternative formulation, using the information-centric terminology introduced in the author’s essay [P2], these behaviour-aware user interfaces utilise *implicit* information assessed for *explicitly* performed user interactions.

3

Behaviour-Aware Mobile Touch Interfaces

This section reflects on our research with a focus on positioning it in the literature. The structure follows the guiding research questions and the resulting three main contribution areas: 1) *analyses and models* of mobile touch (targeting) behaviour, 2) *application areas* for behaviour-aware mobile touch UIs, and 3) *methods and tools* for creating them. Figure 3.1 presents a visual overview.

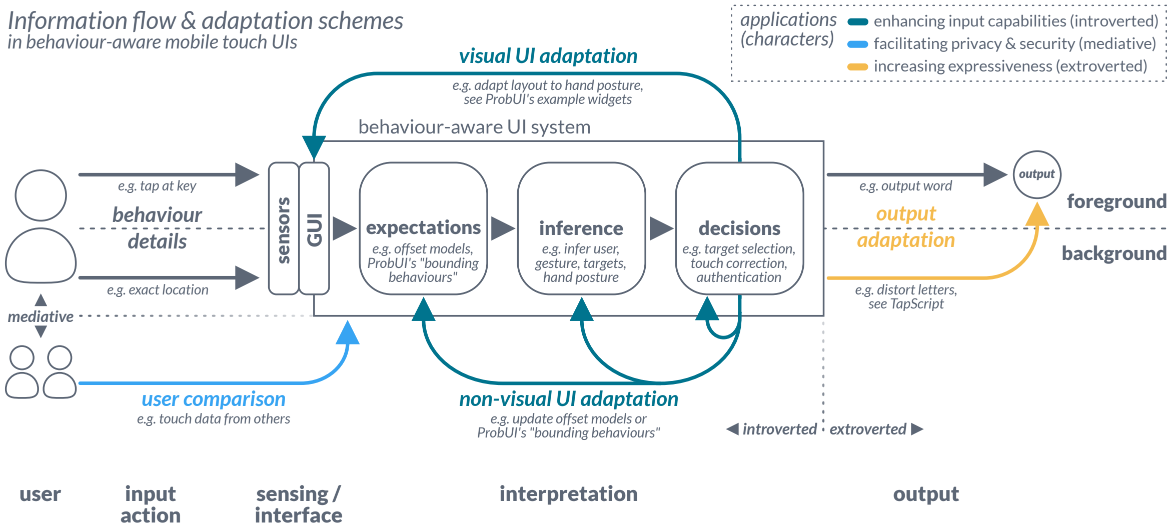

Figure 3.1: Information flow and adaptation schemes in behaviour-aware mobile touch UIs. This figure presents a visual summary highlighting aspects and concepts discussed in this thesis. Note that not all possible information flows are depicted here (e.g. does not show feedback loops back to the user).

3.1 Analysis, Modelling and Inference: Mobile Touch Targeting

3.1.1 Insights into Touch Targeting Behaviour and Modelling

Table 3.1 gives an overview of our investigation into factors which influence touch offset patterns and modelling. Considering related work (also see Table 3.2), we position our research as follows: We are the first 1) to analyse offset patterns and models from the same users across different devices [P10], 2) to investigate the influence of hand postures and GUI targets on offset modelling, considering accuracy improvements and biometric value [P4, P6], and 3) to analyse offset patterns and models for stylus input [P9]. We refer to the original publications for discussions on individual findings. Here, in a broader view, we discuss the main challenges and opportunities for utilising offset patterns and models in practice.

Cate-gory	Factor / Comparison	Findings	References
target	location	Basic factor for offset patterns: offsets depend on location. Screen edges and corners are most relevant for characterising targeting behaviour patterns.	Buschek et al. [P4, P9, P10], Weir et al. [159]
target	shape and size	Offset lengths & angles vary more for large targets. Small targets lead to more individual and consistent patterns. Patterns are less posture-specific for large/broad targets.	Buschek et al. [P4, P6]
hand posture	left vs right	Generally mirrored patterns, left vs right hand can be recognised based on offset patterns.	Buschek et al. [P10]
hand posture	thumb vs index finger	Thumb vs index can be recognised based on offset patterns. Index finger input is more accurate than thumb, but less individual. Offset patterns are less similar across hand postures than across target types.	Buschek et al. [P4, P6]
imple-ment	index finger vs stylus	Stylus is more accurate than the finger, yet the extent depends on the screen location. Fingers benefit relatively more from offset corrections than styli. Stylus offset models also improve finger touch, but not vice versa.	Buschek et al. [P9]
stylus	nib type & hover cursor	Stylus width/nib affects offset patterns more than the hover cursor. A thin plastic nib glides more and in a more complex pattern than a thick nib (and the finger).	Buschek et al. [P9]
mobility	sitting vs walking	Offsets are larger while walking (i.e. less accurate targeting). Implement (stylus vs finger) has a stronger influence on offset patterns than mobility.	Buschek et al. [P9]
device	phone model (size)	Offset patterns contain device-specific and user-specific aspects. Combining them allows us to transfer a user-specific offset pattern across devices.	Buschek et al. [P10]
hand	size	Small hands tend to show larger vertical offsets near the top of the screen, yet shorter ones near its bottom.	Buschek and Alt [P4]

Table 3.1: Overview of our investigation of factors influencing touch offset patterns (and modelling), with a short summary of our main findings.

Challenges: Dealing with Variability in Offset Patterns

Throughout our studies, we found that offset models improve touch accuracy under a variety of influences and conditions. This is the case for different GUI targets, hand postures and fingers, styli, and while walking. In that sense, offset patterns and models can be considered as fairly robust. However, our analyses also showed that these models ideally should be trained on touches collected under the same conditions. In the worst case, they might otherwise even lead to worse accuracy; for example, finger offset models should not be applied to correct stylus touches [P9]. Thus, specific offset patterns and models are not robust across all contexts. Since mobile touch devices are used in a variety of everyday situations, this is a main obstacle for utilising offset patterns and models for improving touch accuracy in practice. To address this, our insights point towards several directions:

First, we could train models on touches from a variety of contexts. For the 2D offset models discussed here, this would likely lead to simpler patterns and consequently more "conservative" predictions (cf. [63]). The data collected across all our studies could be combined to support such efforts.

Second, we could use (stronger) regularisation via the models' hyperparamters to push the model towards more careful predictions which might improve generalisation across contexts.

Third, we could take models from contexts known to be more robust. For example, we found that stylus models also improve finger touch [P9], partly since a stylus is more accurate and the resulting models thus predict smaller (i.e. more "conservative") corrections. Similarly, posture-specific models (thumb vs index finger) work across different GUI target sizes for the same posture [P6].

Fourth, we could combine models in a "chain of responsibility" pattern, similar to the concept for touch keyboard models by Yin et al. [170]. This would require detecting the current context to use the most specific model available. For example, the system might store one model for index finger use and another one for the thumb. Detecting the current posture then allows the system to determine which model to use for correcting current touches. Touch behaviour itself already helps to detect such contexts (shown by our work and others, see Table 3.3), and future devices might employ other sensors to facilitate this further (e.g. around-device touch sensing [97, 108, 109, 110]). We thus plan to build such a hierarchical model in future work and evaluate it in the wild under varying contexts.

Finally, we could directly integrate context data into the offset model as a predictor. Related work showed this for gait phase [113] and acceleration [115] (Table 3.2). Considering the strong influence of different hand postures revealed in our studies, (further) grip and posture-related data seems a particularly promising addition to investigate in the future. With more information beyond the touchscreen, the 2D offset pattern models might then be viewed as (part of) a more general approach of mapping behaviour patterns to input points. This can also be seen as extending general (touch-based) mappings, for example investigated for users with motor impairments (e.g. *Smart Touch* [111]).

Opportunities: Utilising Variability in Offset Patterns

On the other hand, offset pattern variability need not be bad news for applications – it can also be seen as an opportunity for gathering information. Indeed, our investigated applications (Section 3.2.2) are motivated by exploiting such variability in touch input behaviour.

Besides the context factors discussed in the previous section, *individual users* are the main factor influencing offset patterns. Throughout our projects, we observed that mobile touch targeting behaviour is highly individual [P1, P4, P5, P6, P7, P9, P10]. This confirms results from related work [160]. Beyond prior work, we explicitly analysed individuality of offset patterns and studied how such user-specific behaviour is influenced by factors like hand postures and GUI targets [P6] and implement [P9]. Based on our findings, we conclude that this individuality opens up opportunities for utilising the discussed variability in offset patterns, in particular for user authentication and identification (also see sections 3.1.3 and 3.2).

We can look beyond individuality with a similar perspective: The previous section discussed the context-specific nature of offset patterns as a challenge for accuracy improvement. For other applications, however, this might be seen as an opportunity. For example, we proposed a concept [P4, P6, P10] for detecting hand postures and fingers in use based on differing offset patterns under these conditions (see Section 3.1.3). Moreover, our *TapScript* project exploited the variability in offset patterns while typing in different contexts to subtly reveal such contexts to messaging partners [P8].

Summary: Targeting Behaviour Insights

Regarding analyses of targeting offset patterns and models, this thesis research contributes novel insights, analysing: 1) patterns of the same users across devices, 2) influences of hand postures and GUI targets, and 3) offset patterns and models for stylus tapping. Moreover, our results highlight variability in offset patterns, which presents a challenge for practical touch accuracy improvement, yet also an opportunity for utilising these patterns, for example to distinguish users and contexts or to communicate context.

Name	Input	Output	Model/Method	Parameters	References
Offset Cursor	vertical touch location (y)	intended vertical touch location (y)	constant offset added	constant offset in y only	Potter et al. [125], Sears and Shneiderman [142]
Shift Correction Vector	past touch down-up distances	intended touch location (x, y)	constant offset added, updated per touch	w updating weight	Vogel et al. [156]
Polynomial Offset Model	touch location (x, y separate)	intended touch location (x, y separate)	polynomial function	coefficients of two fifth order polynomials	Henze et al. [63]
Linear Offset Model	touch location (x, y)	2D Gaussian describing likely intended locations (x, y)	quadratic function	coefficients of two quadratic polynomials	Buschek et al. [P10, P4]
GP Offset Model	touch location (x, y)	2D Gaussian describing likely intended locations (x, y)	one Gaussian Process regression model	GP hyperparameters	Weir et al. [160]
RVM Offset Model	touch location (x, y)	intended touch location (x, y)	Relevance Vector Machine	RVM hyperparameters	Weir et al. [159]
XY + Grip Offset Model	touch location (x, y), device acceleration and rotation (500 ms before touch)	intended touch location (x, y separate)	two GP regression models (x, y separate)	GP hyperparameters	Negulescu et al. [115]
Gait Phase GP Offset Model	touch location, acceleration (from which gait phase is estimated)	intended touch location (x, y separate)	two GP regression models (x, y separate), gait phase estimation algorithm	GP hyperparameters	Musić et al. [113]
Inverse Offset Model	target location (x, y separate), target width/height	2D Gaussian describing likely touch locations (x, y)	linear/GP regression	coefficients / GP hyperparameters, ε noise scaling	Buschek et al. [21, P6]
Change Point Offset Model	sequence of touch locations (x, y)	probability of behaviour change per timestep (e.g. user change)	polynomial functions	coefficients of polynomials	Buschek [P1]

Table 3.2: Overview of touch offset models.

3.1.2 Touch Offset Models

Beyond using touch offset models to analyse behaviour patterns, we also contribute to offset modelling itself. To position our work, Table 3.2 presents an overview of related research. In the following, we discuss our contributions regarding three key aspects.

Informing Modelling Decisions

We proposed a *"2D" linear model* [P10]; it uses both dimensions x, y for its predictions for both x, y. Earlier work had either investigated a linear model using each dimension separately (i.e. x/y only predicted based on x/y respectively) [63] or a non-linear model [160]. Taking into account all our studies, we found that using both x, y is important (e.g. see [P10]), yet linear models are often expressive enough (with appropriate basis functions) to improve touch accuracy. They offer practical benefits compared to the non-linear Gaussian Process (GP) models, most importantly faster training and a much smaller memory footprint, which enables handling very large datasets. On the other hand, we found that the GP models' greater flexibility makes them a much better choice for our inference method, in particular for user authentication/identification [P6].

Inverse Offset Models

We proposed the *inverse* use of offset models, that is, predicting likely touch locations for a given target location. In particular, we used this to simulate touch behaviour for given GUI layouts [P6], in order to estimate their biometric value. To do so, we embedded the inverse offset models into a probabilistic touch interaction model that sampled users, hand postures, targets, and finally touch locations. Beyond this application, such generated touch behaviour might also prove useful as a proxy for real user interaction for other analyses or computational GUI optimisation (cf. [121]). As another application scenario, we used inverse models for predicting and analysing touch behaviour on mobile websites [21]. We investigated inverse offset modelling with our 2D linear model [21] and the GP model [P6]. However, our concept is flexible and could also be used with other offset models from related work (see Table 3.2).

A Change Point Offset Model

We proposed and evaluated a *change point offset model* [P1], based on change point estimation with linear models [128]. In light of the related work, this is the first offset model to explicitly consider touches as sequences with behaviour changes. It embeds linear models to detect changes in model parameters and outputs a probability of such a change per timestep. In particular, we evaluated this for detecting and locating user changes (also see Section 3.1.3).

Summary: Modelling

Regarding modelling mobile touch behaviour, this thesis research 1) informs model choices for touch offset modelling, 2) enables computational simulation of (spatial) touch targeting behaviour for mobile GUIs via inverse offset models, and 3) extends offset modelling to utilise touch sequences with change points.

3.1.3 Inference on Mobile Touch Targeting Behaviour

Using touch offset data and models, we also investigated inferring further information about user and context. To position our work on such inference, Table 3.3 gives a broad overview of work on inferring different kinds of information from mobile touch behaviour. We discuss our contributions regarding three aspects.

Inference Using Touch Offset Patterns

We provide and investigate an *inference method for touch offset models* to infer information based on touch targeting (offset) patterns [P4, P6, P10]: We evaluate observed touch offsets using the predictions (i.e. expectations) of models trained on previously recorded touches per class (e.g. left

Information	Interaction	Features and Sensors	Models and Methods
intended target	tapping	touch location (x, y)	2D Gaussian per target [56], two 2D Gaussians per target (FFitts' Law [14]), Bayes' rule (Bayesian Touch Criterion) [15], other methods e.g. for users with motor impairments (e.g. *Smart Touch* [111])
intended text	typing	touch sequence (x, y), language context, IMU [53]	2D Gaussians, n-gram language model, Bayes' rule [53, 56], Gaussians with restricted support [57], abs./rel. location mapping [127], model graph [170], decision trees [53], shape-based [90, 91, 154, 173].
user	tapping, typing, scrolling, gestures, other (non-touch, e.g. device pick-up [110])	touch offset [P7, P6, 41], size [P7, 41, 169, 174], location [P7], distance [P7, 81], drag [P7, 41], gesture features [20, 37, 47, 51, 133], pressure [P7, 41, 169, 174], IMU [41, 144, 174]	offset models [P7, P6], template matching [37, 47, 133, 151, 174] / k-nearest neighbours [P7, 144], decision trees [34], Bayes nets and Naive Bayes [P7, 81, 114], logistic regression [34], NN [134, 144], SVM [20, 51, 144, 169] and other kernel methods [P7]
hand posture	tapping, typing, scrolling, gestures	touch offset [P4, P10], size [54], timing [54, 170], distance [170], gesture features [98], capacitive sensors [67] also around the device [28, 119, 171]	offset models [P4, P10], heuristics [28, 54], k-nearest neighbours [98], SVM [170]
finger orientation	tapping	cap. (touch) sensors [104, 131, 168], depth-camera [89]	particle filter [131], Gaussian Process [168], heuristics [168], CNN [104]
finger pressure / "force"	tapping	touch area [17, 43, 55, 129], IMU [55, 65, 70, 77, 147], microphone [78, 79], magnetometer [76], wrist-worn IMU [163]	special stylus [78, 76], vibration damping [55, 77], DSP and heuristics [65, 70, 79, 147]
unintended touches	tapping, drawing	contact area [5, 71], touch (sequence) features (e.g. speed, no. of events, distance between touches) [100, 141], IMU [100], hover and other stylus-specific information [5]	heuristics [71], decision trees [100, 141], geometric occlusion model [157]
cognitive errors	swiping	cap. sensors (around device) and IMU [109]	Random Forest, SVM [109]
result relevance / satisfaction	zooming, swiping, inactivity	swipe and zoom features (pressure, size, count, distance, etc.) [58, 88, 164]	regression trees [58], decision trees [88], random forest[164]
affect / emotion / stress	tapping, typing, scrolling, swiping	scroll and swipe features (length, speed, pressure, etc.) [29, 52, 143], tap features (pressure, size, drag, number) [29, 143], corrections [29]	several classifiers [29, 52, 143]: SVM, NN, decision trees, Bayes nets, discriminant analysis, kNN, etc.
"truth / lying"	tapping, swiping	timing, touch area, offset, pressure [112]	SVM [112]
sex	swiping	swipe features (length, time, width, height, area, thickness, pressure) [107]	Naive Bayes, logistic regression, SVM, decision tree [107]
age (group, e.g. child vs adult)	tapping, dragging	touch/drag time and distance [153], touch locations and timestamps [66], IMU [36]	Naive Bayes [153], sigma-lognormal neuromotor model [66], DSP plus several classifiers [36]
thumb size	swiping	swipe features (length, time, thickness, pressure, speed, acceleration) [12]	correlations only [12]

Table 3.3: Overview of information inferred from mobile touch interaction behaviour. For each information type, the table shows main models and methods with example references.

vs right hand). This yields a likelihood for each class per touch, which we aggregate over multiple touches. Using this approach, we inferred users [P6, P10] as well as hand and finger/implement in use [P4, P9, P10].

Related work (Table 3.3) inferred hand posture for specific GUIs and tasks (in particular typing [54, 170]) or used extra sensors [28, 119, 171]. In contrast, our approach addresses tapping in general and only requires touch and target locations. On the other hand, reliable inference with such limited features tends to require a greater number of touches [P4, P6, P10]. To address this, future work could apply our inference method to offset models which use further sensor data, in particular those which combine touch and motion sensing ([113, 115], see Table 3.2). One could also combine evidence from our approach on the screen with that from around-device sensors.

Our change point offset model [P1] provides an alternative inference method based on touch offset sequences. This approach allows us to detect and locate behaviour changes in touch targeting sequences. Existing related touch models and methods (Tables 3.2 and 3.3) could be used for change detection as well, yet none of them is explicitly designed to do so. One benefit of our approach using a dedicated change point model is that it does not require training data (detecting change vs recognising previously seen behaviour). Nevertheless, observing a certain number of touches is still required for accurate inference [P1].

Looking ahead, full capacitive array data [67, 104] could facilitate inference. This might be combined with offset models by training them on such data instead of 2D touches. Related work [160] supports this for touch correction; future work could study it also for inferring postures or other information. Moreover, screens with fingerprint sensing (see [72, 73, 148]) promise to greatly improve recognition of users, postures, and fingers. In this light, our approach provides an alternative for users who do not like to submit fingerprints, for devices without such sensors, or for contexts that might not easily have access to them (e.g. websites). Finally, interest in offset-based inference is not exclusively motivated by applied prediction but also by fundamentally *analysing* behaviour: For example, inferring user/posture from offsets yields insights into the user/posture-specific information in pointing behaviour. We argue that this offers value independent of details of screen technology, for example for generative behaviour models (see e.g. our touch simulation [P6]; cf. use of simulation in "Computational Interaction" [124]), or to complement related perspectives on pointing characteristics, like speed-accuracy tradeoffs (e.g. [50, 167]) and endpoint distributions (e.g. [6]).

Touch Offsets as a Feature in Mobile Touch Typing Biometrics

We also examined touch offsets for inference independent of specific touch offset models. In particular, we proposed and evaluated a *new feature set* for touch typing biometrics: We combined touch-specific spatial features (incl. offsets) with the "traditional" temporal ones. Most previous work had not used touch-specific typing features and some related work thus called for new features [33]. Touch typing offsets in particular were not considered, or not evaluated [41], as highlighted in other work [169]. Our results [P7] show that these spatial touch typing features can offer higher biometric value than the temporal ones and thus should be considered in touch typing biometrics. Indeed, touch-specific spatial typing features have recently gained more attention (e.g. see a recent survey on mobile touch biometrics [150]).

We further evaluated these spatial touch features on data collected from users' own "free" typing in the wild [P5]. Compared to our lab results [P7], the difference between spatial and temporal features seemed even more prominent. Our results thus indicate that finger placement is more characteristic and consistent than typing rhythm throughout the varying contexts of real-world mobile typing. Using our logging tool [P5], future studies can further investigate this, for example, with a more diverse user group and long-term observation.

A Framework for Probabilistic Inference in Mobile Touch GUIs

Finally, we took a step towards using touch input behaviour-based inference in practical applications: We contribute *a probabilistic framework for continuously inferring users' intended targets and behaviours* from touch input (*ProbUI* [P3]). This includes both simple taps as well as (a limited class of) touch gestures. Considering related work, *ProbUI* takes ideas from probabilistic target and keyboard models (first two rows in Table 3.3) and adapts them for general mobile touch GUIs. In particular, *ProbUI* uses Gaussians to represent targets, like work on touch keyboards (e.g. [56, 170]). Moreover, targets in *ProbUI* can be represented by more than one behaviour component, similar to the use of two Gaussians in *FFitts' Law* and the *Bayesian Touch Criterion* by Bi et al. [14, 15]. We discuss *ProbUI* in relation to other frameworks in more detail in Section 3.3.3.

Summary: Inference
Regarding inference on mobile touch behaviour, based on several studies, our thesis research contributes: 1) an approach for utilising touch targeting patterns to infer information, such as user, hand, and finger, as well as behaviour changes in targeting sequences; 2) a novel feature set, including touch offsets, for inferring users from mobile touch typing data, with evaluations on static text in the lab and free text in the wild; and 3) a concept and framework for probabilistically inferring intended target and touch behaviours (gestures) in mobile touch GUIs.

3.2 Applications: Personalised, Secure and Expressive Mobile Touch Interaction

In this section, we reflect on application opportunities for behaviour-aware mobile touch interfaces. We first characterise such applications in general, before discussing specific application areas, based on examples from the projects conducted as part of this thesis research.

3.2.1 Characterising Applications of Behaviour-Aware UIs

We first describe application areas on an abstract level. They originated from the author's essay [P2], which highlighted a common interest in user individuality in both biometrics and the concept of "Extended Self" (ES, see Belk [8, 9]). According to ES, people use (digital) objects to define, reflect and communicate their identities. Belk's discussion [9] refers to the functions of Having, Doing, and Being. We related this to systems using behavioural biometric information for security (Having), UI personalisation (Doing) and user representation (Being). In a similar yet broader view, beyond the strong biometrics link of the essay [P2], here we describe application "characters" for behaviour-aware mobile touch interfaces. The use of such terminology for describing "intelligent" UIs takes inspiration from work on smart touch keyboards by Quinn and Zhai [126]. We propose to characterise applications of behaviour-aware UIs with these terms:

- *Introverted* applications utilise behaviour information to adapt to the one person currently interacting with that (part of the) interface. Examples from our work include adapting GUIs (e.g. *ProbUI* [P3]) or touch input interpretation (e.g. user-specific offset models [P4, P9, P10]).
- *Mediative* applications utilise behaviour information related to the existence of multiple users (or the possibility thereof), most often to compare them. For personal mobile touch devices, the most prominent examples of this kind are systems for user identification or authentication, such as our projects on biometrics for targeting [P1, P6] and typing [P5, P7].
- *Extroverted* applications utilise user behaviour information to adapt the output of the user's interactions. Here, "output" does not refer to system feedback but to the user's created digital artefacts. In the mobile touch context, such outputs are often related to communication tasks with other people (e.g. creating a message, see our *TapScript* [P8] project).

3.2.2 Investigated Application Areas

Here, we reflect on behaviour awareness applied in mobile touch UIs with the different described "characters". In particular, we investigated applications regarding 1) UI adaptation, 2) privacy and security, and 3) expressiveness. For brevity, we focus on the relation to prior work as well as highlighting a key consideration for each area.

User Interface Adaptation

Behaviour-aware user interfaces can assess a user's input behaviour to adapt to it. This is an example of an *introverted* application (see Section 3.2.1). Following related work on user-specific adaptation in touch GUIs [49], we investigated two kinds of adaptation:

1. *Adaptation of input interpretation* [P4, P9, P10]: Offset models trained on users' previous touches can be applied to improve touch accuracy. By mapping raw touches to likely intended locations, these models change the way future touches are interpreted. However, this does not visually change the user interface.
2. *Visual GUI adaptation*: In contrast, our work on *ProbUI* [P3] introduced models of touch input into a GUI framework, also to visually adapt the interface. For example, we adapted it to the user's hand posture to improve reachability.

In one sentence, we position our work on UI adaptation as addressing *"influences and integration"* – in more detail: The first application directly continues related research, which also applied touch offset models to correct touches (see related work in Table 3.2). However, we studied these models in further detail with a focus on influencing factors relevant for practical applications, such as hand postures and GUI targets (see Table 3.1 and the related discussion in Section 3.1.1). Beyond offset models, our second project in this application area (*ProbUI* [P3]) contributes a novel concept for integrating touch behaviour models into GUIs – in particular to facilitate UI adaptation. A detailed comparison to related concepts and frameworks is discussed in Section 3.3.3.

Looking beyond this thesis and further towards (long-term) practical deployments, we argue that many relevant questions surrounding adaptation in behaviour-aware (mobile touch) interfaces arise from the choice (or mix) of these adaptation types. In particular, one needs to take into account possible feedback loops between the system's adaptation and the user's.

Related work showed that visual feedback improves touch targeting performance (e.g. [64, 162, 172]), yet the co-evolution of such learning effects under continuously "learning" offset corrections remains to be studied. Work on adaptive touch keyboards found that visual adaptations in particular can result in unfortunate co-evolution leading to heavily distorted and less usable and effective GUIs [49, 57]. Thus, we plan to investigate such feedback loops in dedicated experiments in the future.

Privacy and Security

Relating behaviour-aware UIs to biometrics (see Section 2.4), this application area has historically gained most attention when it comes to assessing and utilising interaction behaviour information. The grand goal is reliable user identification/authentication. This is an example of a *mediative* application (see Section 3.2.1). Table 3.3 (row "user") presents an overview of the different kinds of interactions and behaviour information used in related work.

In one sentence, we position our work in this area as *"facilitating the use of touch offsets and further research"*, explained as follows: We first refer to our contributions related to utilising touch offsets for inferring users from touch behaviour, as discussed in detail in Section 3.1.3. Beyond this, it is important to note in this application section that we did not deploy an actual identification or authentication system "live" and in the wild. This decision to "take a step back" was based on remaining practical challenges revealed by the literature (e.g. dealing with changing hand postures, see our related work and discussions in [P7] and [P5]). Thus, we focused on analyses, methodology, and tools as prerequisites for developing robust future applications:

1. We evaluated, discussed and addressed evaluation schemes [P7] and influencing factors that need to be considered for practical applications, such as the influence of hand postures [P6, P7] and GUI properties [P6].
2. We contribute to methodology and practical research with a concept and tool (*ResearchIME* [P5]) for collecting users' "natural" typing data in the wild, in a privacy-respectful manner. To the best of our knowledge, we are the first to collect such mobile touch typing data (also see related work in [P5]).

Going forward, we plan to further develop and employ our tools to inform robust modelling and new biometric features. Moreover, we plan to assess user perception of such data collection and use, as already started with the *ResearchIME* project [P5].

Expressiveness

Related work on mobile touch input proposed a wide range of ideas to enrich touch and render related interactions more expressive. Table 3.4 shows an overview. Behaviour-aware user interfaces in this area present examples of *extroverted* applications. In one sentence, we position our work on expressiveness as *"revealing the background in the foreground"*, unfolded in the following.

What?	When?	Where?	What for?	Perspective	References
touch area	during touch	on screen	e.g. mode switch (pan vs zoom)	foreground	*Fat Thumb*, Boring et al. [17]
finger/stylus pressure	during touch	on screen	e.g. mode switch, drawing, gaming	foreground	*GripSense*, Goel et al. [55]; Hwang et al. [76, 77, 78, 79]
hand posture (discrete)	several touches	on screen, device	e.g. adaptive keyboard [54]	background	*GripSense*, *ContextType*, Goel et al. [54, 55]
hand hover posture	before touch	above screen	e.g. targeting, GUI adaptation	fore/background	Hinckley et al. [67]
grip changes	before/after touch	on device	e.g. anticipating touches [108, 115], detecting errors [109], identifying users [110]	background	Mohd Noor et al. [108, 109, 110], Negulescu et al. [115]
hand contact shape	during touch	on screen	e.g. mode switch	foreground	*TouchTools*, Harrison et al. [61]
finger orientation	during touch	on/above screen	e.g. pan, zoom, rotate; occlusion-aware UIs [131]	fore/background	Mayer et al. [104], Rogers et al. [131], Xiao et al. [168]
finger parts	on touch	on screen	e.g. different modes	foreground	*TapSense*, Harrison et al. [60]
hand parts (palm)	on touch	on screen	e.g. mode switch	foreground	*PalmTouch*, Le et al. [96]
mid-air finger movement	in between touches	above screen	e.g. mode switch, zoom	foreground	*Air+Touch*, Chen et al. [27]
typing gesture finger movement	during touch	on screen	e.g. font settings	fore/background	Alvina et al. [3]
stylus movement	independent of touch	above/around device	e.g. drawing, gestures	foreground	*MagPen*, Hwang et al. [76]
device movement	during touch	on screen, device	e.g. mode switch, zoom, touch context	fore/background	Hinckley and Song [70]
arm/wrist movement	before/during touch	above/on screen	e.g. rotation, scrolling, gaming, mode switch	fore/background	*Expressy*, Wilkinson et al. [163]
device movement and orientation; keystroke duration, pressure, finger placement (offsets)	before/during/ between touches	on screen, device	font adaptation	fore/background	*TapScript*, Buschek et al. [P8]

Table 3.4: Overview of touch behaviour information (first column) utilised for "rich" and expressive mobile touch interaction in related work and in *TapScript* [P8] (last row).

As the table shows, many projects are motivated by using the additional information in the foreground, that is, as dimensions intentionally controlled by the user (also see Section 2.4). Some discuss both foreground and background perspectives (e.g. see Hinckley et al. [67, 70]) and others focus on the background (e.g. see the use of grip changes by Mohd Noor et al. [108, 109, 110]). Related, motivations for both foreground and background use can also be found in research on inferring specific information from touch input (see Table 3.3).

Our perspective on expressiveness in *TapScript* [P8] originated from the idea of revealing background behaviour information to the users by influencing the output of the foreground interaction in which said information is assessed. This view differs from using information either in foreground *or* background. It is also different from most projects that consider both foreground/background in that we focus on adapting output (message fonts in *TapScript*) – in contrast to adapting the GUI or input interpretation (e.g. cf. Hinckley et al. [67, 70]).

Foreground and background uses then intersect: Once behaviour aspects affect output, users may start to intentionally control them, thus bringing them to the foreground. We indeed observed this in *TapScript* [P8]: For example, a participant reported that the font's tilt communicated lying on the couch (background), whereas they later on intentionally controlled the tilt to highlight words like *italic* markup (foreground). Related work on gesture keyboards later examined such control aspects more directly, supporting our interest in this view: Alvina et al. [3] found that users could intentionally vary previously "uncontrolled" background aspects of their interaction when these were revealed in the foreground output. In particular, users controlled gesture features such as speed and inflation to modify font properties. In what could be regarded as a foreground alternative, Alvina et al. also studied shortcut gestures [2] which included controlling font properties.

Based on such work as well as our own experiences with *TapScript* [P8], we regard the assessment and use of the "background in the foreground" as an interesting direction for further exploration of expressive interaction via behaviour-aware UIs, for mobile touch devices and beyond. In particular, one may investigate in detail the conditions, evolution, and (long-term) consequences of transitioning from uncontrolled background influences to controlled dimensions of the foreground interaction's output in "expressive" behaviour-aware UIs.

3.2.3 Behaviour Awareness Across Applications and Devices

The presented application areas may benefit from sharing behaviour information and models between them, as also discussed in the author's essay [P2]. The projects contributing to this thesis motivate such a vision of transferring and (re)using behaviour information and models. In particular, we used touch offset patterns and models across applications: 1) They help to improve touch accuracy [P4, P6, P9, P10], 2) they can be used to distinguish people based on targeting [P1, P6] and typing [P1, P5, P7], and 3) they allow us to personalise output (fonts) [P8]. Instead of collecting data and training models per application, future systems might thus share such data and models. As an example from the literature, Löchtefeld et al. [98] used touch data collected during device unlocking to infer hand posture. This information could then be used to adapt UIs in other apps on this device in this session.

We did not explicitly examine such cross-application transfer. Reflecting on our work, it seems likely that models require different settings and schemes per application. For instance, *TapScript*'s offset model [P8] needed to reflect current finger placement to dynamically adapt the font. It was thus updated based on a short history of recent touches. In contrast, correcting touches to improve accuracy usually benefits from larger training sets [P10, 159]. More generally, the (re)use of behaviour information across behaviour-aware UIs thus requires careful further investigation. We return to this in the conclusion (Section 4).

Moreover, behaviour information and models might be shared *across devices*. We contribute the first study of cross-device transfer of personal mobile touch behaviour information for touch targeting models on smartphones [P10]. We represent devices *implicitly* by how they influence the modelled behaviour. Thus, to reuse behaviour information, we require no knowledge about devices themselves, such as physical properties or internal algorithms. We can instead directly refer to behaviour differences between these devices, even if these are observed for other users. While our study is limited to different smartphones, future work could investigate this and similar approaches for transferring touch behaviour models between phones, tablets, and smartwatches.

Summary: Applications

Regarding applications of behaviour-aware mobile touch UIs, our research contributes: 1) a perspective motivating the use of behaviour information across different areas, in particular beyond security; 2) an exploration of three application areas for behaviour-aware UIs with different "characters"; 3) reflections on using touch behaviour information across applications and a concept for transferring offset models across devices.

3.3 Methods and Tools for Behaviour-Aware Mobile Touch UIs

Several projects contributing to this thesis resulted in the creation of frameworks and tools. Here, we discuss them in the light of related work.

3.3.1 Collecting Mobile Touch Typing Data in the Wild

We regard studying user (input) behaviour as an important first step to develop and create behaviour-aware user interfaces. To facilitate this for our context, we contribute a concept and tool to collect mobile touch typing data in the wild in a privacy-respecting manner [P5].

More concretely, we provide an Android keyboard app, *ResearchIME*, that records typing touches. To avoid logging readable private text, we introduce a sampling-based filter. In particular, our study [P5] used a *random n-gram* filter: It logs text-revealing information for n subsequent touches with a small chance (we used 10 % and $n = 3$) and a minimum gap between subsequent loggings. Text-revealing data for the remaining keyboard touches is not logged ("redacted").

To position this concept in the literature, Table 3.5 presents an overview of the main related logging methods for typing data. The list is limited to methods which 1) could also be used for mobile typing beyond the lab, and 2) offer an inherent degree of privacy protection. Note that other variations, methods and tools exist, for example for generally developing further loggers (e.g. the *AWARE* framework [48]).

Our sampling concept and tool differs from related work in two key aspects: First, it collects and retains both *temporal* touch features (and touch order) as well as *spatial* ones. This is motivated by our literature survey on the required and desirable touch typing information in related research (see related work in our paper on *ResearchIME* [P5]), and our prior investigation [P7] on the benefits of combining those features in typing biometrics (also see Section 3.1.3). Second, our concept and tool

Logging Method / Example Ref.	Description	Pro	Contra
Experience Sampling Method (ESM), Reyal et al. [130]	ESM app on participants' own devices that prompts several transcription tasks per day	no interference with private typing; typing information in varying real world contexts over several days	limited to given text; in Android: no access to spatial touch features (e.g. exact x, y); does not observe users' own "natural" typing
Custom app and tasks, Kumar et al. [92]	logging typing (and swiping) for given tasks in a modified web browser app	no interference with private browsing; "full" information within the custom browser	limited to one browser and given tasks; in Android: no access to spatial touch features; does not observe users' own "natural" typing
Custom keyboard and tasks, Alotaibi et al. [1]	logging typing for given tasks in a modified keyboard app	no interference with private typing; access to spatial features; typing across apps	limited to given tasks; does not observe users' own "natural" typing
Typing game, Henze et al. [64]	logging typing in a game app with a modified keyboard	no interference with private typing; access to spatial features; potentially large amount of data (game as motivation)	limited to the game; does not observe users' own "natural" typing
Common words, Dowland and Furnell [40]	logging full information for the top 200 common English words	full data for whole words; some degree of text obfuscation	might reveal private text; bias by chosen words; language-specific; problems with (chat) slang / colloq. language
Dummy characters, Evans and Wobbrock [45]	key logger replaces all characters with a fixed dummy ("m")	no text can be reconstructed; full temporal/order information	no character/key-specific information
Shuffling, Draffin et al. [41]	text obfuscated by removing touch timestamps and shuffling the data	no text can be reconstructed; locations and keys logged for all touches	neither temporal nor sequence (order) information

Table 3.5: Overview of main related methods which have been – or could be – used for collecting mobile touch typing data beyond the lab with (a degree of) privacy protection.

enable the collection of these features from *users' own free text typing* (i.e. "natural" behaviour) – in contrast to transcribing given text or typing in given ("artificial") tasks.

As a main limitation, our logging approach replaces users' usual keyboard app in order to get access to all typing features across all apps (also see our discussion in the paper [P5]).

3.3.2 Modelling Touch Targeting Behaviour

Our *TouchML* [P4] toolkit implements linear and non-linear offset models used in our research [P4, P6, P9, P10, 160], as well as visualisations and metrics to evaluate them. It is the first open-source implementation of these models tailored to the mobile touch and HCI context (libraries with general regression models are of course widely available). We hope to facilitate more widespread use of (touch) offset modelling, as an extension to other models (e.g. Fitts' Law models [167]). Recent related work on mobile stylus input called for further exploration of "the diverse and complex nature of accuracy" [4]. In targeting analyses, offset models help to assess underlying *spatial* patterns in detail. Our comparison of finger and stylus tapping behaviour [P9] presents one example of considering such patterns to analyse and compare input methods. Besides such analytical use, the toolkit also facilitates building applications using offset models (in Python, JavaScript, Android).

The toolkit is not limited to touch; these models can be applied to any 2D targeting data, for example distant pointing [59, 155]. The models could also accommodate targeting in 3D, which might be interesting, for example, for pointing in virtual reality (cf. [105]). Beyond the published research projects, it is worth mentioning that we successfully employed the toolkit as teaching material to support several student theses and research projects, as well as practical workshops and lectures (at LMU Munich[1] and Munich University of Applied Sciences[2]). It was also used in another published research project combining touch and Kinect data to understand and address parallax effects on public displays [84].

Related to *TouchML* [P4], we modelled targeting behaviour to estimate touch locations for GUI layouts, for example to evaluate their biometric value [P6] or to predict potential usability issues [21]. While this concept is not part of the toolkit, *TouchML*'s offset models can be used to implement it.

3.3.3 Building Behaviour-Aware Mobile Touch GUIs

Our *ProbUI* [P3] framework contributes and implements a concept for facilitating the creation of behaviour-aware mobile touch GUIs. In particular, it facilitates building GUIs with probabilistic "expectations" about input behaviour. These are used to inform feedback and adaptation, based on the user's current behaviour.

To position *ProbUI* in the literature, we recall its core contribution – it conceptually and practically integrates three key areas into one framework: 1) declarative definition of input behaviour (touch gestures), 2) probabilistic modelling of said behaviour, and 3) probabilistic reasoning based on those models during interaction. In more detail, Table 3.6 lists influences as well as similarities and differences of *ProbUI* compared to other related frameworks from those three areas. Bringing them together, *ProbUI* combines the ease-of-use of declarative definition of input behaviour with the benefits of probabilistic reasoning.

As a key step to enable this combination, *ProbUI* automatically maps the developers' deterministic behaviour declarations to probabilistic input models. This concept separates *ProbUI* from its most closely related work: 1) declarative gesture languages (e.g. *Proton* [86, 87]), which do not yield probabilistic models; and 2) probabilistic GUI frameworks (e.g. see the work by Schwarz et al. [138, 139, 140]), which focus on handling existing probabilistic input representations (e.g. provided by external gesture recognisers [139]).

As a downside of enabling this combination, *ProbUI* is limited in depth in the specific areas: 1) It provides no graphical editor and (currently) offers less expressive declarations (cf. *Proton* [86, 87]); 2) it supports less complex gestures than dedicated editors using demonstration and learning from data (e.g. *Gesture Coder / Studio* [101, 102]); and 3) its probabilistic approach focuses on input representation and does not inherently cover the whole GUI state (cf. Schwarz et al. [139, 140]).

Multiple probabilistic models per target also appear in *FFitts' Law* by Bi et al. [14], with a similar application to target selection in the *Bayesian Touch Criterion* by Bi and Zhai [15]. An equivalent setup can be realised in *ProbUI* by attaching two "tap" behaviours per target with parameters as in the related work. However, *ProbUI* is originally intended to deal with conceptually different behaviours

[1] `http://www.medien.ifi.lmu.de/lehre/ss17/ath/`

[2] `http://www.medien.ifi.lmu.de/lehre/ws1718/ups/`

Framework / Reference	Description	Similarities to / influence on *ProbUI*	Main difference to *ProbUI*
GDL [85]	declarative language for (multi)touch gestures	declaration of gestures; referencing and connecting them in (boolean) rules	no probabilities; gestures not tied to GUI targets
Midas [137]	declarative language for (multi)touch gestures	same as above; general link of rules and GUI elements	no probabilities
Proton [86]	declarative language for (multi)touch gestures, similar to regular expressions	declarative language inspired by regular expressions	no probabilities; gestures not tied to GUI targets
Proton++ [87]	extends *Proton* [86], e.g. with directional expressions	symbols describe sequence of finger movements	same as above; direction symbols relative to finger, not GUI target
Gesture Coder / Studio [101, 102]	GUI tool for developing multitouch gesture recognisers using demonstration and a video editing metaphor	automatically deriving internal recognition models from developers' input	GUI; uses training data; programming by demonstration
Gesture Script [99]	GUI tool for developing unistroke gesture recognisers using demonstration combined with a scripting language	same as above; developer specifies sequence of gesture parts	GUI; uses training data and demonstration; procedural code ("scripts", not declarations)
Grafiti [38]	framework for gesture management and GUI integration	attaching gestures to specific GUI targets; more than one gesture per target	gesture recognisers need to be coded manually
Schwarz et al. [138]	framework for prob. handling uncertain input in GUIs	distributing input events to all GUI targets; prob. mediation concept for reaching decisions	assumes existing input prob., e.g. from external recogniser
Schwarz et al. [139]	framework for prob. handling uncertain input and GUI states, while retaining deterministic event handlers	same as above; motivation to reduce "probabilistic details" that developers need to think about	same as above; sampling-based inference; prob. model inherently includes GUI state
Schwarz et al. [140]	architecture for generating and fusing possibly suitable GUI variations during interaction in prob. GUIs	motivation to utilise input behaviour probabilities to provide rich "live" feedback during interaction	focus on handling prob. GUI states; sampling-based inference

Table 3.6: Overview of related frameworks – which influenced *ProbUI*– for modelling, recognising, and inference on (mobile) touch input behaviour.

(e.g. swipe left vs right), or execution styles (e.g. scroll with thumb vs index), and not components of variability for one (e.g. absolute & relative tap precision in *FFitts' Law* [14]). Finally, *ProbUI* is related to adaptive touch keyboards, which also probabilistically model expected input (touches per key, see e.g. [22, 57, 170]). *ProbUI* generalises this idea, embedding expectations about touch inputs into general GUIs beyond the keyboard, and accounting for touch gestures, not exclusively taps.

Summary: Methods and Tools

To facilitate building and evaluating behaviour-aware mobile touch UIs, we contribute: 1) *ResearchIME*, a concept and tool to facilitate privacy-respectful collection of typing behaviour data in the wild; 2) *TouchML*, a toolkit that provides offset models for analytic and constructive use, plus visualisations and metrics for evaluation; 3) *ProbUI*, a concept and implemented framework for creating behaviour-aware mobile touch GUIs, in particular with probabilistic input expectations and related UI adaptations.

3.4 Limitations

Participants

Most participants were recruited via channels related to the university. They might not represent the wider population in every aspect. Touch behaviour also varies across age groups [66, 153] and for users with motor control disabilities [26, 111]. We highlighted individual behaviour in our analyses (e.g. [P6]) and conceptual reflections [P2]. We believe that behaviour-aware mobile touch UIs have the opportunity to address more specific user groups than the ones we have investigated so far.

User Studies

We mostly conducted lab studies (Table 1.2), since they allowed us to study specific factors under controlled conditions in detail [P4, P6, P9, P10]. This comes with some limitations: First, we studied targeting behaviour on provided smartphones – and in the case of typing with given passwords [P7]. It is possible that this influenced participants' behaviour, compared to their usual devices and passwords. Results such as offset patterns thus might underestimate characteristics developed over long term use. However, all our studies required repeated tasks (targeting [P4, P6, P9, P10], password typing [P7]). This is a common way of simulating routine behaviour (see e.g. overview of input repetitions for typing biometrics in the survey by Teh et al. [149]).

Second, lab studies typically assess behaviour at one point in time. However, consistency and change in behaviour are relevant for behaviour-aware UIs. To address this, our lab studies involved two sessions in different weeks (TAPS-I, TAPS-II, TAPS-STYLUS, PWD-TYPING). However, more extended observation periods are desirable to capture long-term behaviour changes. Anecdotally, in additional experiments related to the TAPS-I study we observed strong changes in targeting behaviour over the course of two months for a user who only then started to use a smartphone in their daily live. Moreover, in TAPS-II [P6] and PWD-TYPING [P7], we showed that evaluations based on a single session are overly optimistic. These observations and results motivate more long term data collection.

Finally, lab studies only involve a limited set of contexts. While we included different hand postures and mobility contexts (sitting, walking), everyday life presents a greater variety of interaction situations (e.g. encumbrance [116, 118, 117], "juggling" objects [122], ambient temperature [136]; also see the recent overview by Sarsenbayeva et al. [135]). Hence, our results might not generalise to all these situations. Nevertheless, for offset models, related work indicated that they can improve accuracy even on a large scale with unknown contexts [63].

However, besides these lab studies, we also studied behaviour in the wild, in particular related to text messaging and typing (TAPSCRIPT-CHAT, TYPING-WILD). Moreover, with our *ResearchIME* [P5] concept and tool we facilitate further studies beyond the lab (see Section 3.3.1).

User Experience

Our studies assessed user experience only to a very limited extent, that is, mostly regarding perception of the study tasks and tools (e.g. [P5, P9]). In contrast, for example, we did not study how offset corrections are *experienced* by users in mobile touch interactions in their daily lives. One practical challenge here is integration into a mobile OS. A future study could employ experience sampling methods to assess whether increased touch accuracy is actually (positively) experienced as such by users in the wild. Complementary, perception of "failure cases" in everyday life is interesting as well, in particular since offset models improve average accuracy, not necessarily every single touch.

Modelling

We used linear regression [P4, P10], also as part of a change point model [P1], Gaussian Processes [P4, P6, P9], and Relevance Vector Machines [P6] to model touch targeting behaviour in terms of offsets. We employed Hidden Markov Models to represent touch gestures in *ProbUI* [P3]. We also examined several classifiers and anomaly detectors in typing biometrics [P7]. While these choices were motivated by related work (e.g. [13, 15, 63, 149, 160]), other models and variations could be examined as well. As a main conceptual limitation, we only captured *physical* behaviour aspects. We did not address *cognitive* models (cf. [83]). In particular in *ProbUI* [P3], for inferring intended target and use of GUI widgets, it would be interesting to consider the user's decision making as well.

We set model parameters either by training on collected study data [P4, P6, P7, P9, P10], or – as part of *ProbUI*'s contribution [P3] – based on strong assumptions tied to GUI target properties (location, size) and developer input. We did not infer parameters during interaction, with the exception of the Gaussian Process offset model in *TapScript* [P8]. However, here models adapted the font and did not directly alter ongoing touch behaviour.

These limitations point to two extensions: 1) inferring parameters during interaction; and 2) examining feedback loops for live adaptations of behaviour-aware interfaces. Promising inference methods for the former include particle filtering (e.g. [25, 131]), Markov Chain Monte Carlo (e.g. [139]), and approximate Bayesian computation (e.g. [83]). For the second direction, related work [103, 140, 165] and our observations with adaptive widgets in *ProbUI* [P3] highlight the importance of (visual) feedback, also considering uncertainty. On the other hand, there are known cases where visual adaptation is undesirable (see section 3.2.2). Thus, live inference and model updating along with appropriate feedback present important research directions for behaviour-aware (mobile touch) interfaces.

Devices and Hardware

Our projects employed off-the-shelf devices and thus did not explore custom hardware prototypes. Hence, we did not investigate novel form factors, sensors, and so on. On the other hand, this focus highlights the potential of closely examining input behaviour for common devices, namely unmodified smartphones. Moreover, our *TapScript* field study [P8] in particular benefited from running on users' own commodity devices, since our prototype was thus better integrated into people's usual daily messaging. Finally, focusing on off-the-shelf devices supports fast adoption of research results.

In future work, we plan to consider further sensing for behaviour-aware interfaces on mobile touch devices. In particular, recent related research shows two promising directions: 1) extending touchscreens by utilising the full capacitive array of sensor data, for example for "pre-touch sensing" [67]; and 2) adding additional touch sensors on the back and sides of the device, for example to assess (tablet) grip location [28] and posture [171], to anticipate future touches [108], and to recognise cognitive errors [109].

4 Conclusion

Variety, within the limits of satisfactory constraints, may be a desirable end in itself, among other reasons, because it permits us to attach value to the search as well as its outcome [...].

Herbert A. Simon, The Sciences of the Artificial, 1996

4.1 Reflection

We conclude with a critical reflection, starting with the question: Why are behaviour-aware mobile touch UIs interesting and worth investigating? A high-level answer involves *information*: If input behaviour were precise and constant, it would not be very informative to observe its details – we would already know what to expect in advance. In such a world, designers and developers might perfectly well "hardcode" expectations directly into the UI. We are clearly not living in such a boring world: In our studies, we observed rich user-specific and context-specific variations in input behaviour, even for such a seemingly trivial task as tapping a touchscreen button. Thus, behaviour-aware mobile touch interfaces offer the opportunity to gather non-trivial information, in particular related to user and context. This opportunity fundamentally motivates our interest in behaviour-aware UIs and related models and inference.

However, gathering information alone says little about the value of such UIs for the users. There may be other ways to obtain such information. Why would someone care about having a behaviour-aware mobile touch inferface? In a sense, this behaviour information comes for free: Users need to perform input behaviour "anyway", for their main task. Thus, inferring information from said behaviour may, for example, save users' time and reduce distraction, compared to asking them to provide this information explicitly (e.g. implicit vs explicit authentication). Phrasing this more abstractly (and taking on an information transmission perspective on HCI [74]), "throughput" might be increased not exclusively by investigating new or refined interaction techniques and devices, but also by utilising more of the information that is already contained in input actions. To address the question of usefulness further, we need to consider more specifically how UIs can utilise input behaviour information. To do so, our thesis research explored three application directions. In particular, we showed that behaviour-aware mobile touch UIs can 1) improve touch accuracy, 2) support (implicit) user identification and authentication, and 3) render keyboards and messaging more personal and expressive.

Together, our projects on touch offsets also demonstrate that (the same) input behaviour information and models can be used across applications and devices. We return to our essay [P2] to illustrate potential benefits with an example: To improve a system's usability/security trade-off, we typically focus on security-related UIs; behaviour information either 1) adds a security layer (e.g. "hardening" passwords [P7] / patterns [37]), or 2) replaces explicit action (e.g. implicit continuous authentication [35]), albeit potentially adding an enrolment phase. In contrast, transfer of behaviour information and models across behaviour-aware UIs promises to impact on a system's usability and security in a broader view: The system could exploit information collected in security-related interactions to improve usability in others. For instance, a device might detect hand postures during unlock (e.g. via touches for PINs/patterns) to adapt the UI (cf. Löchtefeld et al. [98]); for example, keyboard (cf. *ContextType* [54]), homescreen, and specific widgets (e.g. *ProbUI* [P3]).

More generally, transfer of behaviour information and models seems particularly relevant with respect to visions of ubiquitous computing environments [132, 161] in which users move between – and interact with – a multitude of interconnected devices as they move through their day. In conclusion, we envision *comprehensive* behaviour awareness, which separates the loci of behaviour assessment and consideration via transfer and reuse of behaviour information[1].

Finally, which role might behaviour-aware UIs play in future HCI research and practice? In this regard, we highlight their use for *embedding expectations* about user input. We have alluded to a view of "expectations" at several points in this thesis already; now we conclude by extracting the underlying perspective as an outlook.

Expectations about user behaviour arise, for example, from user research or data and experiences with previous systems. Good design will likely reflect these expectations (e.g. to address the needs of a specific target group). We envision that the locus of these expectations (further) shifts from developers and designers to both humans and artefacts: With behaviour-aware UIs, they can give their expectations a representation *embedded into the artefact itself.* Instead of anticipating behaviour only at design time, the artefact itself then also actively shapes and utilises expectations during use.

This might align with a similar shift at an earlier step, as described in Simon's seminal *Sciences of the Artificial* [146]: Computational optimisation shifts parts of the ("low-level") decision making from designers to an (interactive) computational system (also see e.g. [121, 124]). Behaviour awareness further shifts the use of expectations to the system, namely after it has been deployed to the user.

User behaviour models linked to UI adaptations and (re)actions have been paramount in visions of intelligent user interfaces for many years (see e.g. [18, 24, 158]). A related panel at the CHI '17 conference asked: *"To what extent should a machine try to understand a person in real time versus simply embodying the understanding of its human designers?"* [46] In this context, behaviour-aware UIs cast as embedded expectations set a focus on *anticipating and reacting to input behaviour characteristics during use*. In our view, this promises to better account for diverse individuals and changing contexts, which might be difficult to comprehensively anticipate and address in a static design up front. We also see such embedded expectations about user input as a way of integrating computational intelligence into HCI in a more collaborative role, that is, without *replacing* user input like in a full-on agent view.

It is worth looking beyond HCI to find that this focus on expectations about input fits well to Predictive Processing [30], which states that perception starts with predicting one's own expected sensor inputs. Learning from comparison with actual sensations refines an internal world model, which informs future actions. One may draw parallels to behaviour-aware UIs as conceived in this thesis: They model expected input characteristics (e.g. touch offsets, Section 3.1.2), they conduct inference via comparisons with actual interactions (Section 3.1.3), and they have the capability to react accordingly (e.g. adaptation in *ProbUI* [P3]). These components are also highlighted in our overview in

[1] As a concrete outlook, these ideas significantly contributed to two granted projects, leading to further investigations by a new research group in Munich: The *Biometrics++* project is funded by the Bavarian State Ministry of Education, Science and the Arts in the framework of the Centre Digitisation.Bavaria (ZD.B). The *Ubihave* project is supported by the Deutsche Forschungsgemeinschaft (DFG), Grant No. AL 1899/2-1.

Figure 3.1. Is this analogy more than a philosophical sidenote? Yes – this view provides a perspective on perception (i.e. for UIs: input handling) and may guide us in embedding expectations into UIs. We see it as a focus on input behaviour, on (generative) models which enable UIs to "imagine" it, on considering uncertainty and continuous input – to name three key aspects (cf. [30]).

This thesis demonstrates ideas for taking up this view in HCI, most prominently combined in the framing and concepts of *ProbUI* [P3]. We believe that these ideas are relevant on a broader scale: For example, UIs which are behaviour-aware in this Predictive Processing view fit well to concepts and perspectives in the emerging focus area and practical toolbox of "Computational Interaction" [124]. For example, they might be particularly interesting with regard to UI optimisation [121], since they bring along embedded usage simulations (see e.g. our touch interaction simulation in [P6]). Looking beyond this thesis, we plan to explore behaviour-aware UIs further, guided by this perspective.

4.2 Future Work

Looking ahead, we outline several concrete ideas for continuing the work of this thesis.

Simulating touch targeting behaviour: We used inverse offset models to predict likely touch locations for given targets and thus GUIs. We employed this to estimate biometric value of touch GUIs [P6] and also explored applications for identifying usability issues with mobile websites [21]. This could be examined and evaluated in more detail. Simulating touch behaviour might then prove useful as a component in computational optimisation of touch GUIs, for example regarding layouts [121, 152].

Keyboard use in the wild: As a fairly direct next step, we plan to continue with the *ResearchIME* [P5] project. The tool offers several study opportunities (also see the paper [P5]), including: 1) a large-scale and/or long-term deployment to analyse typing behaviour, biometrics, and keyboard use in the wild on a larger sample; 2) a study on novel keyboard designs or modifications to analyse influences on user behaviour and performance (e.g. a second row of word suggestions or swapping keys, cf. [16]); 3) a study with new (and/or gradually changing) keyboard layouts to analyse learning curves and possibly inform learning strategies and models with everyday typing data (cf. [82]).

Utilising touch beyond points: Beyond touch as 2D points, we plan to utilise richer touch(screen) data, such as capacitive images. Recent related work already shows interesting ideas for using this information (e.g. [67, 104]). This data could serve as input to offset models (cf. [160]). Since full capacitive data provides more information than a 2D point, this might improve inference with these models – and inference on touch behaviour in general. We showed the value of spatial touch features for user identification [P7, P6]; considering the full capacitive array might further improve on this (e.g. in keystroke biometrics). Moreover, we could adapt *ProbUI* [P3] to use such data as its input instead of touch points. This promises to further facilitate recognition of different touch behaviour variations (e.g. hand postures) and subsequent GUI adaptations. In addition, full capacitive data allows for new kinds of touch interactions and variations (e.g. angle, approach; see [67, 104, 131]). This renders *ProbUI*'s concepts for building GUI elements which react to multiple touch behaviours all the more relevant. Finally, this additional information might be used for expressive interaction: For example, *TapScript* [P8] could consider the typing finger's angle for font adaptations as well.

Transfer and reuse across applications and devices: As outlined in this thesis, behaviour awareness need not be limited to a single view, app, or device. We plan to investigate this further, for example, by studying transfer methods for concrete cross-application cases (e.g. from unlock interaction to homescreen or keyboard, cf. [98]), also beyond the touchscreen (e.g. detecting context during device pick-up). Other device combinations can be considered as well (e.g. smartwatches [27], rings [31], other wearables). One result could be a matrix of promising combinations of behaviour information sources and targets. This is planned as one part of the mentioned project (*Biometrics++*).

User experience, concerns, and views: Beyond *TapScript* [P8] and *ProbUI* [P3], and general feedback throughout our studies, we have not yet investigated user experience and views of behaviour-aware UIs in detail (also see Section 3.4). Important aspects for future work include: 1) *perceived impact* of behaviour awareness – for example, regarding touch correction and GUI adaptations; 2) *user concerns* about (re)using behaviour information across applications and devices; 3) *transparency and awareness* – for example, how to communicate to users which behaviour data is assessed and (re)used? The latter aspects in particular are also investigated in the *Biometrics++* project (see [106]).

Feedback loops: As mentioned in Section 3.2.2 and Section 3.4, opportunities for further work include investigations of the co-adaptation of user and behaviour-aware UIs, which use live adaptations and updates of input interpretation and GUI. For example, we could study how visualising the corrected touch location affects the user's future targeting behaviour – thus changing the pattern underlying the correction, possibly requiring model updates. In general, it is interesting to study if and under which conditions such loops result in improving or deteriorating user performance.

Specific user groups: Since they assess and utilise (individual) variations in input behaviour, behaviour-aware UIs seem particularly interesting for addressing specific user groups (see Section 3.4), for example senior users or people with motor control disabilities. We see two main aspects for future investigations: 1) recognising such user groups based on input behaviour (e.g. age detection based on touch input [36, 66, 153]); and 2) adapting the UI and/or content for them.

Behaviour awareness beyond physical aspects: Considering behaviour details need not be limited to physical aspects. Future work on behaviour-aware UIs might further include models of cognitive aspects [83], for example to estimate the utility of certain input behaviours in certain situations (also see Section 3.4). This presents a way of extending inference, for instance, in our *ProbUI* [P3] framework.

Behaviour awarenes beyond mobile touch interaction: Conceptually, the notion of behaviour-aware UIs is not limited to mobile touch interfaces. More concretely, several aspects of this research could be investigated in other contexts as well: Analysing, modelling and predicting offset patterns might be useful for other input modalities. For instance, future work could further investigate offset patterns for distant pointing on a wall or for mid-air pointing in 3D UIs (e.g. in AR and VR environments), as started in recent related work [105]. Moreover, ProbUI's concepts are not limited to touch and its "bounding behaviours" could be extended to enable GUI elements to expect and react to other modalities. For example, this might include moving, rotating or shaking a device (cf. the *Resonant Bits* concept [10]), gaze input (cf. smooth pursuit interfaces [44]), or even sound and speech. Finally, utilising details of input behaviour could increase expressiveness in other modalities than touch, such as mid-air gestures (cf. [25]).

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References

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Eidesstattliche Versicherung

(Siehe Promotionsordnung vom 12.07.11, § 8, Abs. 2 Pkt. 5)

Hiermit erkläre ich an Eidesstatt, dass die Dissertation von mir selbstständig und ohne unerlaubte Beihilfe angefertigt wurde.

München, den 9.5.2018

Daniel Buschek