Informing the Design of User-adaptive Mobile Language Learning Applications

Christina Schneegass, Nađa Terzimehić
LMU Munich, Germany
firstname.lastname@ifi.lmu.de

Mariam Nettah
LMU Munich, Germany
mariam.nettah@campus.lmu.de

Stefan Schneegass
University of Duisburg-Essen, Germany
stefan.schneegass@uni-due.de

ABSTRACT
Smartphones enable people to learn new languages whenever and wherever they want. This popularized mobile language learning apps (MLLAs) and in particular micro learning that offers simple and short learning units to keep the user on track. Due to the ubiquitous use of these applications, they have to adapt to the users' current situation to provide an optimal learning experience. To gain insights into how users perceive common usage scenarios, we conducted an online survey (N=74) and clustered all described learning scenarios into five categories of usage situations. We outlined internal and contextual factors which are characteristic for these situations and discussed those in a follow-up focus group with HCI experts (N=4). During this focus group, we collected four design recommendations to adapt MLLAs to situations of users' (a) high attention levels, (b) tiredness or exhaustion, (c) highly demanding environments, or (d) low motivation.

CCS Concepts
•**Human-centered computing** → **Ubiquitous and mobile computing design and evaluation methods;** *Ubiquitous and mobile computing systems and tools;*

Author Keywords
Mobile Learning; User Adaption; Context-aware Learning; Cognition-aware Learning

INTRODUCTION
The ubiquity of smartphones popularized mobile language learning applications (MLLAs) which offer simple and short language learning units. These applications have proven to be a feasible tool to learn new languages [15, 27]. Although these applications have the advantage of time and location independent learning [32], today's MLLAs rarely adapt to the requirements of different usage situations.

Within this work, we make first steps towards investigating how MLLAs could be adapted based on user's current contextual situation and cognitive capacities. Since we aim to optimize users' individual learning processes, we chose not to rely on technical tracking solutions, but on individual user perceptions and experiences. Hence, we conducted an online survey on the actual usage behavior of MLLAs, in order to derive frequently occurring learning scenarios with the focus on usage context (e.g., location or setting) and cognitive properties (e.g., attention or stress level). We subsequently clustered the usage situations into five common situations, as can be seen in Figure 1. Furthermore, we conducted a focus group with HCI experts, which complements the list of factors influencing MLLA usage and derives ideas for adaption according to certain factors. Based on the fused results, we present four design recommendations for user-adaptive MLLAs to (a) enhance user engagement, (b) target high attention levels, (c) deal with highly demanding environments, and (d) keep up user's motivation. This list is not exhaustive, but highlights currently underrepresented yet promising aspects to support the creation of user-adaptive MLLAs.

The contributions of this paper are twofold. First, we derive and characterize 5 common usage scenarios for mobile language learning from an online survey (N = 74). Second, we present design recommendations for user-adaptive language learning to customize applications to everyday usage situations.

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MOBILE LANGUAGE LEARNING
Recent improvements in mobile technology, together with the trend of short learning sessions, made language learning become more ubiquitous. Hence, the usage of and research on MLLAs steadily increased, fostering learning anytime and anywhere [28]. With further advancements in sensor technology and interaction techniques, research often takes the user's situational context into account. Thus, context is gathered to create a personalized learning environment adapted to the characteristics of each individual learner [13].

Micro Learning
In the past decade, mobile language learning followed a trend towards micro learning (ML) applications, i.e. micro-content delivered in micro-interactions to help users learn without information overload [3]. This is especially useful when applications are used in contexts which are likely to have distractions or interruptions (e.g., on a subway ride). A well-known example for this is the application *Duolingo*[1].

[1]The Duolingo App: https://www.duolingo.com/, last visited August 10, 2018

The concept of ML bases on psychological research stating that repetitions are more effective for learning a new language than long streaks [9]. Research on ML has shown, that people often engage in short learning sessions when mobile and highlights the feasibility of ML in idle moments such as waiting situations [12]. A central problem ubiquitous learning applications entail is the variety of usage situations. To provide an optimal learning experience in a variety of situations, applications need to be adapted to the users and their context.

User Adaption in Mobile Learning

Learning applications are adapted according to a variety of factors. The most common differentiation when describing learning applications is according to users' context or cognition. The term *Context* describes users changing properties and can be subdivided into, among others, users' physical, temporal, task, social, or technical context [20]. An example for adaption based on users' location is to present learning contents based on a building the user is passing by [17]. In addition to external factors, user's internal states (e.g., cognition or emotion), are important.

Human cognition is described as a sum of "[...] processes and structures for perception and attention, memory, thinking and problem solving, learning as well as speech comprehension and speech production." [2]. The following sections present an excerpt of user adaption mechanisms in mobile learning according to frequently targeted cognitive or contextual factors.

Cognitive Load

One of the most extensively researched facets of human cognition is cognitive load (CL). Besides others, the complexity, amount, and presentation of the material [24], as well as internal processes such as users' circadian rhythm [21] induce CL during the learning process. CL can either be measured directly via subjective ratings, a variety of physiological measurements such as pupil dilation and heart rate [8] or via behavioral patterns, e.g., smartphone usage [11]. Bulling et al. [6] investigated eye-movements, in particular the feasibility of recognizing visual memory recall, to assess a person's CL in learning tasks.

Attention & Interruption research

When using mobile learning applications, users additionally have to focus on their surroundings or might even be on the move at the same time. Thus, they can not pay attention for the learning process. In comparison to traditional classroom learning, in mobile learning we are more likely to divide our attention between several tasks. The system OneMind applies an algorithm for detecting divided attention on mobile phones via camera-based heart rate tracking. Xiao & Wang [30] found that internal divided attention has a significant negative effect on learning outcomes. Researchers tried to address this problem by detecting so-called 'breakpoints' between two actions [25] to find opportune moments for notifications. EEG data can give indications of current attention levels, as for example during learning instructions [22] or to show low-attention periods during video lecture [7]. Research on mobile notifications indicates an avoidance of a negative effect on performance by choosing opportune moments, e.g., during times of low CL [18].

Motivation & Engagement

In terms of user engagement, the area of physiological sensing shows us devices which continuously get more precise and implementable in real world contexts. For example, the FOCUS project [16] facilitates EEG data to detect children's level of engagement while reading. By providing learning sessions, FOCUS has shown to significantly improve engagement.

Due to its informality, mobile learning in general is often powered by intrinsic motivation [19]. Demouy et al. discovered in their survey, that user's often engage in mobile language learning out of curiosity for the technology and because they expect it to be entertaining and interactive [10]. In contrast to this overall motivation, research does not consider motivation for short-term engagement with an application. However, mood is known to have an effect on participants choosing to either participate in a structured or vocabulary learning session [10].

UNDERSTANDING USER BEHAVIOR

To learn more about how users perceive their surroundings and internal states in common usage situations, we conducted an online survey. In the online survey, users had to state at least two common situations in which they use a language learning application. To characterize those situations, the survey offered a table to fill in additional details regarding the learning situations. Besides general information on location, time of the day, device, duration, planning, and frequency as performed in [10], the survey asked for five additional facets:

- What is the noise level of the surroundings?
- What is the user's learning company in the situation?
- Is the user situated in a public or private setting?
- Is the user performing additional activities during learning?
- What is the users' stress level?

Sample

We recruited 162 participants via our university mailing list and social media. However, only 74 (54 female, age range between 17 and 32, $M = 23.30$; $SD = 4.33$) fully completed the survey and stated to have used mobile language learning apps at some point in the past. Aside from 3, all had at least a high school degree (28 even a bachelor degree, 14 a master degree, and 1 PhD). Of these 74 participants, most of them were students (64 %) or young professionals. We found these to be a representative group, as students strive to learn new languages for various reasons, as for fun, vacation, or student exchange. Since this study was conducted in Germany (but presented in the English language), the sample also contained international students wanting to learn or improve their German skills. The participants stated to speak at least two and max five different languages ($M = 3.95$; $SD = 0.93$) on various proficiency levels (i.e. basic to native). As their first language, 55 people stated German, and 19 participants stated another native language such as English, Russian, or Turkish. The most common second language was English with 54 occurrences. In total, participants spoke 28 different languages.

[2]Definition translated from Spektrum Psychology Encyclopedia [1]

			Home		Public Transport		Indoors	
			Public	Private	Public	Private	Public	Private
with company	Planned	Low Stress	0	1	0	0	0	0
		Mid Stress	0	0	1	0	3	0
		High Stress	0	0	0	0	0	0
	Not Planned	Low Stress	1	9	0	0	0	0
		Mid Stress	0	2	0	0	0	0
		High Stress	0	0	0	0	0	1
without company	Planned	Low Stress	1	22	4	2	0	1
		Mid Stress	0	1	8	0	0	0
		High Stress	0	0	0	0	0	1
	Not Planned	Low Stress	1	31	9	3	1	0
		Mid Stress	0	5	12	1	1	1
		High Stress	0	0	3	0	0	0

Figure 1. The five clusters of situations according to the dimensions location, company, planning, stress level, and setting.

Results
74 participants characterized in total 131 situations. The *location* in which most of the learning situations happen is home (74), followed by public transportation (44). Few participants stated public places such as library (4), or university (3). *Noise level* got characterized as low, medium and high to very-high 61, 38 and 32 times respectively.

When looking at the *time of the day*, the majority of the described learning situations occur in the evening (51). Still, many participants characterized scenarios where they learn in the morning (39) or in the afternoon. Less often, learning happens at noon (8) or at night (5). Smartphone is the preferred learning tool in 98 of the outlined situations, compared to tablet and laptop, in the category *device*.

We further looked into the *duration* of learning situations. 93 of the characterized situations last 5 - 20 minutes. The overall range is from 5 to 150 minutes. In 111 situations, participants have no *company* while learning and in most of the situations a low to medium *stress level* (123).

The participants reported *planning* roughly one third of all situations in advance (43) and estimated the situations' *occurrence frequency* as daily (39) or at least once a week (60). This indicates an overall high usage frequency. The participants stated accomplishing various additional activities during the use of MLLAs, as watching TV/video/Netflix (19), riding public transport (39), or eating/drinking (5).

Clusters of Usage Situations
We clustered the situations based on (1) user's company (yes/no, where e.g., strangers in public transport were not counted as company), (2) whether the learning session was planned ahead or not, (3) user's perceived stress level (low, medium, and high), and (4) the location itself, i.e. home, public transport, or otherwise indoors. Additionally, we differentiate if the location is public or private, (whereas, e.g., public at home could mean the participant shares home with other people). This clustering resulted in 5 situations, marked numerically from 1 to 5 in Figure 1, covering 82% percent of all situations described in the survey.

In **#1**, the user mainly uses a smartphone to learn. The session mostly occurs in the evening at least several times a week, if not daily. It takes on average 16.36 minutes (SD = 12.06).

In **#2**, users mix between different devices, learning mainly in the evenings, and less often in the mornings. The situation's frequency is daily to sometimes, lasting 29.20 minutes on average (SD = 19.08).

In **#3** depicts a situation in which users learn almost exclusively on their smartphone, not specifically in the morning or in the evening, with a daily to several-times-a-week frequency. The average duration of such a session is 17.49 minutes (SD = 10.89).

In **#4**, users exclusively learn with a smartphone, in the morning and less frequently in the afternoon. A rather noisy environment characterizes these sessions. Users learn daily to several times a week, for (M = 15.05) minutes (SD = 5.88).

In **#5** showcases a situation in a public, indoor setting, such as university, library or train. The noise level is low. For learning, both laptops and smartphones are used. Depending on the user, this situation spans over a daily to weekly usage, and takes (M = 21.67) minutes (SD = 2.88).

EXPLORING DESIGN OPPORTUNITIES FOR HCI
Based on the online survey we outlined questions for a focus group to come up with design recommendations for adaptive MLLAs. Four HCI experts, with expertise in, but not limited to, mobile learning, interface design, security and privacy, and decision support, participated. After outlining the topic, we presented the following four questions:

1. Which internal and external factors influence the user when learning languages on a mobile phone and why?
2. Categorize these influencing factors according to whether they are external (contextual) and / or internal (cognitive).
3. Each pick the one where you expect the highest benefit on learning success and one with the highest benefit for user engagement.
4. Think of ways the (design for the) application could adapt to changes occurring based on the factors derived in step 2.

The first open question revealed a variety of factors influencing learning on a mobile device. The participants of the focus group clustered those in the second question into 13 broad categories, whereof 5 referred to internal processes (*mood*, *motivation*, *boredom*, *curiosity*, *cognitive load*) and 7 target external or contextual factors (*weather*, *social*, *interruptions & distractions*, *location*, *hardware*, *comfort*, *privacy*, *necessity* (e.g., when speaking english fluently is required for work). Considering the highest benefit for the learning outcome, the participants chose *cognitive load*. In contrast, they expected *motivation* to have the highest benefit on users' engagement.

DESIGN RECOMMENDATIONS

Based on the results of both online survey and focus group, we derived at set of design recommendations. This list is not meant to be exhaustive, but is derived to highlight currently underrepresented but promising aspects in frequently occurring usage situations.

React to Tiredness or Exhaustion

Various factors influence the use of an application including its content and relevance, but also the context, available attentional resources, and long-term behavior of the users [23]. As already proven in the Yerkes-Dodsen law, there is an empirical relationship between a user's arousal and task performance [31]. Therefore, adapting for example the difficulty to increase users' attention and maximize performance [29] is not a new insight. However, the focus group revealed the possibility that users may not strive to maximize performance in situations of low attention because of tiredness or exhaustion. A participant suggested adapting the exercise type on the user's attention level. When attention is high, it could offer exercises, which demand more user initiative (e.g., typing whole sentences). In contrast, we recommend presenting exercises with low user initiative (e.g., multiple choice, drag and drop) when the user is tired since interactivity has proven to increase participants' attention time [14].

Within our survey data, we were not able to draw conclusions about users' modality preferences when being tired. Therefore, we suggest supplementing this survey by combining perceived usage characteristics with features of the app the person is currently using.

Target High Attention Levels

In general, the application should make use of levels of high attention and focus. High concentration increases the chance of information being stored in the long-term memory [26]. In many environments, as for example public transport, split attention is inevitable. Bulling recognized focusing on managing user attention by turning continuous partial attention into sustained attention as an important challenge [5].

By displaying contents which infer high attention of the user (as interactive tasks [14]), we could support the user in sustaining high attention levels. During the focus group, participants suggested to moreover individualize this process and investigate changes in users' attention levels in regards to their current situation. Exercise types or topics could be perceived differently between people. When looking at the most common usage situations of our survey, high attention is often occurring with the absence of distractions and interruptions, which are most likely to take place in private environments. In 24 situations users stated to be at home with a low stress level. We recommend targeting these situations to present information which needs to be stored in the long-term memory.

Adapt to Highly Demanding Environments

Controlled experiences have already shown that interruptions have a highly disruptive effect on task performance, error rate, as well as affective state [2]. When the users are already facing a high cognitive load induced by their environment, participants of the focus group suggested reducing the amount of new content. If the users' focus is not solely on the application, the interface should be less cluttered and contain a clear structure. This also applies in situations where the user is tired and therefore has problems to focus. When looking at the situations described in the survey, environments that often demand the user's attention can be found during high noise levels or high stress level. In general, public environments demand more attention than private, as long as users reduce parallel activities to a minimum. As a design recommendation we propose to introduce 'attention grabbers' or visual cues in a public and busy environment, since they have proven to restore context if focus is lost [18].

Keep up User Motivation

The discussion of the focus group confirmed the importance of user motivation on the implementation of MLLAs as already pointed out by literature (see related work). The participants of the focus group suggested increasing gamification elements over time to target drops in users' intrinsic motivation. In addition, when attention and memory capacity decline, the exercises should get easier to end the lesson with a 'happy feeling', since a positive mood has a reportedly positive effect on learning [4]. We suggest tracking the users' situational mood and recommend proposing content along the results of Demouy et al.[10]. Moreover, keeping in mind the users' emotional states can benefit the recommendations of contents.

CONCLUSION

Within this work, we gain a deeper understanding of the users' surrounding and inward factors that influence their usage of MLLAs. First, we distributed an online survey (N=74) to gather insights on users' habits and routines in using MLLA with the aim of deriving common usage situations (i.e., scenarios) in which adapting MLLAs might make sense. The online survey resulted in five clusters of situations that differ besides others in their location, stress level, and private or public setting. A focus group with four HCI experts was conducted to complement the findings from the survey and collect design ideas for adapting MLLAs to certain context changes. The focus group concluded that motivation and cognitive load are the most important factors to adapt for with the goal of user engagement, i.e. learning outcome with a MLLA, respectively. Finally, based on the fused findings from both parts of our research (i.e., online survey and focus group), we derived four recommendations for user-adaptions in MLLAs. We further discussed how adaptations could target, besides others, the MLLA's exercise modality, content, or design.

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