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What does it mean to be good at using a mobile device? An investigation of three levels of experience and skill

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Abstract

An increasing number of computer users lack formal training in operating their devices. These daily users cannot be described as novices or experts within the predominant view of expertise. In order to describe and better understand this type of self-taught intermediate level of skill, 10 casual users of a high-end smartphone series were compared to 10 novices and 4 professionals (help desk personnel) in their learning histories, task performance, and cognitive outcomes. Our study suggests that this type of self-taught intermediate level of skill is device-specific. Experienced users (casual users and experts) exhibited superior performance for representative tasks. This is mainly attributable to faster navigation and better knowledge of interface terminology, not to deeper conceptual representation of the problems. Interviews suggest that this skill is the consequence of routine use and three recurring learning events: familiarization, following of media, and ad hoc problem-solving situations. We conclude by discussing why intermediate levels of skill deserve more attention in HCI research.

Keywords: Mobile devices; Deliberate practice; Skill; Casual users

> "*I have always wished that my computer would be as easy to use as my telephone. My wish has come true. I no longer know how to use my telephone.*"—*Bjarne Stroustrup*

1. Introduction

With the emergence of the Personal Computer (PC) in the 1980s, the World Wide Web in the 1990s, and the mobile device in the 2000s, the majority of present-day computer users hardly fit the classic *expert–novice* dichotomy. These users do not rely on their electronic devices as their primary tools for professions and their associated skills are not tested or certified. They rarely, if ever, read manuals—few computers even offer printed manuals any more. They never receive formal training in their use, and regular users are generally known to be unwilling to invest effort into mastering their devices.

In this paper, we examine users of high-end mobile phones, called *smartphones*, as an instance of this broader phenomenon. The smartphone is the most rapidly growing platform of computers, soon comparable to PCs in numbers: there is a forecast of 1.6 billion smartphone users in 2013, comparable to the current estimate of two billion PCs (Gartner Group, 2008). These phones are approaching PCs in technical sophistication and computational power. Earlier phones were quite simple—so simple that the question of skill differences was only marginally relevant when compared to other domains, such as computer programming where large differences have been observed among individuals (Mayer, 1997). However, the present-day phones feature wireless connectivity, multimedia presentation and capture, a built-in Web browser, full programmability, application installation, a file management system, several gigabytes of storage, location and movement sensors, and high-resolution displays. For example, the Nokia N95

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model, which is studied in this paper, has 64 applications with 395 (unique) options and sub-applications with factory settings, and users typically install more applications with additional options. Consequently it is hardly surprising that developers are concerned about the complexity of these devices—it may limit the perceived usefulness of the devices (Koivumäki et al., 2008) and reduce the willingness to upgrade to newer models (Sugai, 2007). This issue has societal implications as well, because smartphone skills will eventually shape the concepts of the ‘‘digital divide’’ and ‘‘computer-literacy’’ (e.g., Ballantine et al., 2007) and may even affect the intellectual capacities of the world's youth (see Greenfield, 2009).

Traditionally, studies focusing on skill in human–computer interaction (HCI) have tended to compare only the two ends of the continuum of performance, namely novices and experts, while ignoring the groups with intermediate skills (Carroll, 1997; Farrington-Darby and Wilson, 2006; Mayer, 1997). To what extent are *casual users* willing and able to learn how to use the capabilities of their devices? What will they typically learn, how well will they eventually master their device, and what are the acquired cognitive skills that make them different when compared to less proficient novices and to more capable experts? We believe that skill in this domain should be traced to the qualitative characteristics of learning episodes and activities, such as goal-setting, motivations, feedback, persistence, practice design and schedules, etc., rather than in terms of the frequency and cumulated amount of use.

In this paper, we adopt *the expert-performance approach* (Ericsson 2006a, 2006b; Ericsson, 2004; Ericsson et al., 1993; Ericsson and Smith, 1991) to the study of acquired informal skill in using smartphones. In contrast to research on instructional design of training (see van Merriënboer and Kirschner, 2007, for a review), the expert performance approach takes an inductive approach. This approach involves designing a set of representative tasks to permit testing and measurement of individual differences in performance, frequently using groups of people with different employment backgrounds, experience, and formal instruction. By collecting performance and process data, such as think aloud protocols, differences are then related to the mechanisms and cognitive processes that generally mediate superior performance, such as refined mental representations that control performance, speed of execution, and accuracy. In order to understand the differences in the mediating mechanisms, participants are interviewed about their prior experience and their engagement in various related learning and problem-solving activities. When this approach was applied to skills acquired with the help of teachers, such as music and ballet, and skills acquired individually, typically without help of teacher and coaches, such as chess and scrabble, a very consistent set of findings were attained (Ericsson, 2006b). Superior performers in chess tournaments or music competitions had acquired cognitive mechanisms that mediated their superior performance, including their superior performance on representative tasks presented in the laboratory. These mechanisms, in turn, were related to increased amounts of deliberate practice, namely engagement in training to improve certain aspects of one's performance through repetition with feedback and problem solving. A central claim of the expert-performance approach is that the highest levels of performance in a domain are attained as a result of regulated and systematic practice that involves investment of effort, which makes this activity less inherently enjoyable than competing activities. The lower levels of achievement in the same domain are the result of repeatedly executing routine sequences of actions that lead to procedural memory and automatic actions. In contrast to automaticity, deliberate practice leads to cognitive restructuring with memory and attentional skills that enable flexibility and cognitive control of infrequent and non-routine behaviors.

The goal of the present study is to identify and measure reproducibly superior performance for representative tasks in the target domain and then propose mechanisms for accounting for the structure and acquisition of this performance (Ericsson, 2006a). It is an empirical question, whether experienced smartphone users are able to exhibit a performance reliably superior to that of novices, whether they can generate qualitatively better solutions in the tasks (Chi, 2006; Ericsson, 2006a), and whether the types of practice experienced smartphone users have engaged in differs as function of performance (Ericsson, 2006b).

The focus of our empirical study is on *the use of* a smartphone for some purpose as opposed to skills related to its technical functioning. Deliberate practice in the domain of mobile phone use would be viewed as something that goes beyond normal use as simply getting something specific to work, and then recalling the sequence of actions required to do it again in the future. Previous studies of skill in HCI have been criticized for the use of unrepresentative tasks and materials, limiting the generalizability and usefulness of results. For example, expert–novice studies in programming tended to use very short pieces of programming code to represent whole programs and to conduct arbitrary comparisons between various types of code, such as ‘‘structured’’ vs. ‘‘unorganized’’ code (Carroll, 1997). In contrast, our primary goal in designing the experimental tasks was that they represent and warrant generalization to real-world use. The secondary aim was that they should be difficult enough to bring about differences among user groups. Smartphones are unique in that they share several functionalities with both PCs and ordinary phones. They can be used for regular phone activity, such as calling, but also to access the Internet, and they include wireless technologies (e.g., Bluetooth) and complex client–server applications (e.g., games and multimedia). Therefore, tasks were selected so that they measure smartphone use that is unique and differs from the use of ordinary phones and PCs.

In our experiment, 10 casual users of Nokia Symbian S60 smartphones were compared to 10 novices (first-time users with comparable skills in PC use) and 4 professionals (help desk personnel). The particular smartphone operating system, Symbian S60, had 47.1% of the market share at the time of conducting the study in 2008. Verbal ‘‘think aloud'' protocols were collected during task performance. The interview protocol was designed to have casual users' think aloud while they generated solutions to challenging tasks, and their think-aloud protocols were later analyzed to describe differences in problem-solving strategies and concepts. In addition, users were interviewed about their learning histories by using a template derived from the deliberate practice framework.

A ''casual user'' is broadly defined here as a user who does not use the phone for professional purposes (for a discussion of the concept of casual users, see Finstad, 2008). In the absence of a validated measure of expertise in this domain, ''expert'' was here defined by social criteria. We identified several professionals who engage in problem-solving with smartphones on a daily basis as employees by demonstrating and informing customers at a help desk in a telecommunications company. In the absence of certified performance or competitions, we chose this group as the highest perceived level of ''expert users'' of smartphones—given that they are the professional that a regular user would turn to get help. Including the three groups is important, because comparing casual users to novices will allow us to chart the improvement in performance achievable by *regular* use and comparison to professional users to identify the *potential* for further improvement.

1.1. Prior research on skill in everyday computer use

There are no direct studies on regular users' skill in using smartphones that we were able to find. However, because using a smartphone has similarities to the use of other computers, we reviewed available literature on intermediate levels of skill in PC use. Most of these studies have focused on less skilled computer users, such as novices, and somewhat more skilled users, and have rarely studied professional expert users.

The few reports available on casual users' motivations indicate that these users are interested not in understanding the computer *per se* but in how the computer can help them accomplish their primary pursuits. For example, information and communication technology (ICT) skills are mainly acquired informally in homes rather than through formal education in schools (Facer et al., 2001). Young people are motivated to learn ICT to achieve goals that are practical by nature. Furthermore, acquisition of ICT skills seems to be related to peer-group identities and gender. Secondary school students may acquire ''expert roles'' among peers and gain social recognition and prestige (Ilomäki and Rantanen, 2007). However, motivations focused on achieving practical goals with the computer may limit spontaneous understanding of the general aspects of the interface and the structure of the device (Loraas and Diaz, 2009). In a study of ICT learning and emotions, the users expressed happiness most of the time—and anxiety, anger, frustrations, and sadness only sometimes (Kay, 2006). As the users' computer knowledge increased, anxiety and anger levels decreased significantly, which indicates that their attained performance involved primarily familiar activities and thus exploration of new and unfamiliar uses may decrease after the basic functionality is mastered, similar to normal driving, and weekend golf and tennis. Another study has proposed that due to the fact that much of computer and media use involves visual materials, students' verbal skills are not developing on a par with visual-spatial skills (Greenfield, 2009).

Most studies report that self-regulated learning can yield stable improvements, but the nature of underlying cognitive outcomes varies across domains. A study of students' strategies of information search from the Internet found that more experienced students spent more time using their prior knowledge to define the given problem, elaborated on the content, and self-regulated their searches (Brand-Gruwel et al., 2005). In a study of text-editing, secretaries gained knowledge of the interface and become quicker, but there was no evidence that they had learned more efficient ways to control the interface (Rosson, 1983). In a 16-month study of spreadsheet use, there were clear improvements in cognitive components, but these aspects of skill were dependent on memory demands and menu structures (Nilsen et al., 1993). Some users, but not all, exhibited chunking and acquired more efficient methods of performance. The authors concluded that extended experience with software systems does not guarantee that users will even learn the basic functionality. In a study of Web use skills, no evidence was found that the amount of experience would be associated with attainment of skill, as measured by knowledge of interface functionalities (Chadwick-Dias et al., 2004). A recent think-aloud study that compared frequent and infrequent video game players provided tentative evidence of impasse-driven learning in video games (Blumberg et al., 2008). Impasses are moments in problem-solving where information is missing and the current strategy could not provide it. It was found that frequent players had more insights about the game situation and their own strategies than infrequent players, but within the time frame of the experiment both groups increased their problem-solving skills, as evidenced by the proportion of comments reflecting insight, game strategies, and goals.

One reason for lack of progress in the efficiency of computer use may be that intermediate-level users are reluctant to change strategies (Card et al., 1983). It has also been argued (Bhavnani and John, 2000) that users who wish to progress need to learn improved strategies in the intermediate layers of knowledge ''between tasks and tools.'' The essence of these intermediate representations is to exploit specific powers of computers and specifics of the task to construct a new ''integrated'' interaction strategy. Such knowledge is claimed to be general in nature and has wide applicability, but it is difficult to acquire, because the corresponding concepts and knowledge are not directly suggested by tasks or tools. It may be that most users are not willing to invest the energy to develop such representations.

1.2. Everyday skill acquisition as the interplay of motivation, practice, and attention

The theoretical framework of the expert-performance approach was developed to explain the acquisition and outcome of the highest levels of expertise in areas such as music, sports, chess, and academic disciplines (Ericsson, 2006b; Ericsson, 2004; Ericsson et al., 1993; Ericsson and Smith, 1991), where individuals have engaged in focused efforts, or *deliberate practice*, to improve their skills for years and even decades.

It is possible to describe this theory by contrasting it to traditional theoretical accounts of skill acquisition in everyday activities such as driving a car, typing, or playing golf. Whereas the acquisition of expert performance is focused on eventually achieving the highest possible level of performance, people's goals for everyday activities are to reach an acceptable level of performance. In the first phase of learning, acquisition of expert performance (Ericsson, 2006b) may not differ from the natural acquisition of everyday skills (Anderson, 1982; Fitts and Posner, 1967). Beginners try to understand the activity and focus their attention on attaining their immediate goals. In this *initial phase*, errors are perceptually salient and have immediate consequences, such as missing the tennis ball with the racquet and thus causing the end of the rally or being shot down in a video game. These frequent failures reduce the inherent fun of the activity, and often it is a parent or teacher who helps the beginner to succeed.

With more experience (*the middle phase of learning*), gross mistakes become increasingly rare. After a limited period of training and experience – frequently under 50 h for most recreational activities – learners attain an acceptable standard of performance, which can be exhibited with much reduced concentration. Eventually (*the last phase of learning*) learners can elicit their performance without the need to actively control it and it can be described as autonomous (Fitts and Posner, 1967) or a compiled specific task procedure (Anderson, 1982). At this point, most individuals do not perceive a need for further changes, which typically leads to a plateau where the same level of accuracy of performance is maintained for months, years, and decades, requiring mere engagement in regular domain-related activities.

The activities of typical amateurs and many professionals, described just above for the middle and last phase of learning, contrast directly with those of future expert performers, who are not satisfied with attaining merely acceptable level of performance. They keep challenging themselves to achieve an ever higher level of performance all through their development. They continue to design training tasks and set goals just outside the reach of their current performance and thus keep engaging in problem solving, repetition, and gradual refinement of particular aspects that will improve their performance. This type of deliberate practice will depend on the training goals involved and on individuals' pre-existing skills in monitoring and controlling their performance (Ericsson, 2006b). In Table 1, we have summarized the most important qualities.

Expert chess players provide a good example. It is not entirely obvious how skilled chess players can improve their selection of chess moves, especially if they are so good that there is no other chess player in the club that can beat them. For a chess player to make better moves than they would normally do, some other source needs to identify those superior moves. One method used by chess players aspiring to become experts is to buy books with chess games between world-class players. The chess player can then simulate playing against these players by selecting moves for the game—one move at a time. If the chess player makes the same move that the world-class player did then everything is fine. If, however, the player selects a different move than the world-class player, then the player needs to figure out why that move is better. Even more importantly, they need to diagnose why they overlooked the better move and how they can change their search and evaluation processes to select the better move in the same and similar situations in the future.

The central assumption of *deliberate practice* is that an individual's performance in a training task will vary as a function of focus of attention, type of strategy, and many other situational factors. If one wants to reach one's best performance consistently or even exceed one's highest current level, one has to be fully prepared before initiating the practice activity, have access to immediate feedback on the outcome, and then be allowed to repeat the task or perform similar tasks with gradual refinement and modifications.

Performing the practice task under these optimal conditions is much more effective for attaining higher performance than is performing a similar task when it is encountered, frequently unexpectedly, within the natural context of performance (research on instructional design, based on a very different body of research, has reached a similar conclusion, see Van Merriënboer and Kirschner, 2007). For example, imagine an amateur tennis player who misses a volley at the net. Play will continue until sometime later when a similar situation emerges

Table 1
Qualities of deliberate practice (from Ericsson et al., 1993; Ericsson, 2004; Ericsson, 2006b).

Quality	Characterization
1. Motivation	Self-motivated; "To be the best in the field"; the explicit goal is to improve performance
2. Concentration	Full concentration and focus on the study activities
3. Design of practice	In the beginning, practice methods designed by an expert/teacher, learning methods invented in the progress of a career, and the individual's weaknesses systematically explored and focused upon
4. Feedback	Informative feedback on results of performance, acquired or given by a teacher
5. Regularity	Habitual practice at regularly scheduled times
6. Emotions	Not as inherently enjoyable as competing activities

unexpectedly, with a similar problem for the player. Contrast this type of on-the-job learning with a session with a tennis coach. The coach would set up situations where the player would stand at the net and be ready to execute a volley. Upon mastery of the easy volleys, the coach can increase the difficulty of the shots and eventually embed volley shots into the rallies. For complete mastery, it is essential to gradually embed the task in its natural context with regular time constraints and less predictable occurrence.

2. Method

Our study included two parts: (1) interviews focusing on the six sub-components (Table 1) of users' practice, and (2) measurement of task performance while thinking aloud.

2.1. Participants

The background characteristics of the three groups are reported in Table 2. Novices and casual users were recruited with posters and advertisements from companies' and students' e-mail lists.

All members of the *novice* group lacked experience of smartphone use but had at least mediocre (as self-reported) skills with computers and were users of non-programmable cell phones.

The *casual users* were recruited to be regular owners of Symbian smartphones with at least three months (13 months on average) experience in using their current smartphone. Usage of the smartphone was measured by the length of time they had owned the device. The interviews indicated that casual users accessed the smartphone applications, such as the internet and camera, of the phones with sufficient frequency to be valuable to the users.

All novices and casual users reported using laptops and PCs on a daily basis.

The *experts* were two help desk workers and two supervisors of help desk workers in a Finnish communication company. Their daily tasks included helping people with problems with smartphones. We tried to recruit a larger group of experts but the pool of experienced help desk professionals is small and companies are protective of their time and reputation. Our attempts to recruit help desk personnel in other companies were rejected by either their supervisors or the help desk personnel themselves. We believe that reasons for not participating were related to their concerns about the relatively long time required for participation and possibly fears of performing poorly on the representative tasks.

Table 2
Characteristics of the three user groups.

	Novices	Casual users	Experts
Males (%)	50	50	75
Average age	29	31	27
Age range	24–34	26–37	21–33
Education (%)			
Master's degree	40	80	–
Bachelor's degree	60	20	25
Vocational	–	–	50
High school	–	–	25
Phone used in the study	Nokia N95	Various Nokia Symbian S60	Various Nokia Symbian S60
N	10	10	4

2.2. Study design

This study used a between-subjects design. The independent variable was users' expertise: novice (N), casual user (C), and experts (E). Dependent variables were task performance in success rates, completion times, and actions taken during performance. Moreover, verbal protocols were analyzed as described in Section 2.5.

2.3. Tasks

The users performed seven tasks under controlled conditions. The tasks are listed in Fig. 1 and examples of solution paths are given in Appendix A. All tasks required at least 4 selections to be made.

Our tasks were selected based on reports of frequencies of application among smartphone users (Verkasalo, 2009). Verkasalo collected longitudinal logging data from over 1000 users and compiled the main categories of use under 5 categories: Messaging, Browsing, Multimedia, Personal Information Management (PIM), and Voice. The tasks in our study cover three of these: capturing and viewing audio/video are tasks that belong to the category Multimedia; "installing a game" is a task belonging to the category Browsing, as this is done by using a search engine on a browser; the Bluetooth file transfer task and calendar entry tasks fall into the category of PIM. The WiFi/WLAN task does not map on to any single category, but it was included as a recurrent task that enables other uses. We omitted tasks in the categories Voice and Messaging as they are not unique to smartphones.

By default, the tasks were done on a N95 that is a member of the Symbian "family" of mobile operating systems. The novices used a Nokia N95 phone that was provided by the experimenter. The two other groups used their own Symbian S60 smartphones. Since they were all part of the same Symbian S60 series, the phones did not differ in any significant respect from each other.

2.4. Procedure

Participants were instructed to act just as if they were alone and speaking to themselves and were told not to try to explain what they were thinking nor plan what to say—just verbally express their spontaneous thoughts. Participants were given the standard instruction to think aloud (Ericsson, 2002, 2006a), along with a few warm-up tasks that would familiarize them with thinking aloud while completing simple tasks (e.g., "What letter comes immediately after

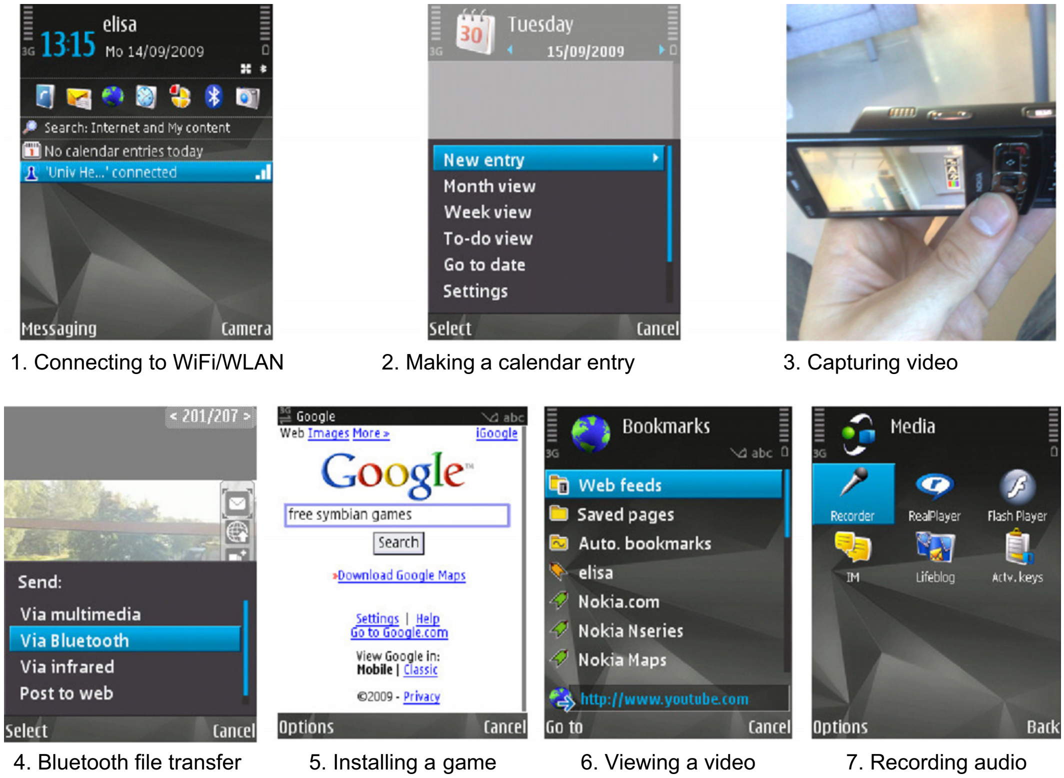

Fig. 1. Seven representative everyday tasks for smartphones used in our experiment to test skilled performance. Images from the Nokia N95.

"A" in the alphabet?" and "What is the fourth letter after 'H'?"). Participants were invited to ask questions about the procedure and given further clarification when requested.

Tasks were videotaped (see Fig. 2) and times to complete the tasks were measured from the video tapes. Any participant who had been trying to complete a task for 10 min was asked whether he or she wanted to stop and move on to the next task. If she wanted to stop, the task was marked as failure. (In the entire study there was only one instance where a participant who wanted to continue beyond the 10 min breakpoint actually solved the problem.)

A limitation in our method is that task success was sometimes randomly affected by uncontrollable technical events affecting the phone. For example, WLAN tasks depend on the WLAN network strength. However, such events happened rarely.

Fig. 2. The setup for tasks. To permit continuous video recording of users' hands and the phone the users were instructed to keep the phone in the area above the white paper.

2.5. Analysis

Learning histories: The tape-recorded interviews were transcribed. Transcripts were analyzed by first tabulating all data according to Table 1 and then encoding frequencies for the different groups. Different categories were created on the basis of the narrative corpus.

Solution strategies: Video data were analyzed for interactive behaviors presented in Table 3 (top section). Optimal solution paths (often several different ones for each task) were identified as the basis for coding.

Think-aloud protocols: Video information was analyzed to understand verbalized references in the think-aloud protocols (Table 3, bottom section).

Task performance: Successful task completion and the associated completion times were recorded from the video footage.

Several iterations of data analysis and discussions among the co-authors were required to develop a coding manual for

Table 3
Categories for video data and verbal protocols.

Category	Description
Behavioral	
Directly useful action	Acting on the optimal solution path
Using a shortcut	Sub-category of the previous but using a shortcut key
Physical exploration	Exploring the smartphone in the hand
Accidental button presses	Pressing a button accompanied by pondering of what happened
Unintended button	Trying to execute a command but pressing the wrong button
Deviation from optimal path	Executing a command with the correct goal but that leads to deviation from the optimal path
Unnecessary subtask	Executing an entire procedure that is unnecessary for the task (e.g., pairing Bluetooth devices before sending a file)
Cognitive	
Reporting an action	Reporting what is currently being done (e.g., "I'll turn on Bluetooth")
Testing	Reporting *testing* something (uncertainty of outcome)
Question	Asking a question on the functioning or use of the smartphone
Uncertainty	Explicitly stating uncertainty about what should be done; using words such as "maybe" or "perhaps"
Inferring the user interface	Making an inference on symbols presented in the user interface
Technical explanations	Explaining, by referring to technical features, why the phone is functioning in a certain way
Specific functionality	Explaining that the smartphone functions in a certain manner because it is a certain type
Anticipation or correct statement	Making an explicit and correct statement on certain functionality of the phone
Confidence	Stating that doing something is, e.g., easy or familiar
Recalling	Referring to one's memory of things
Other devices	Making reference to other computer devices
Wrong rule	Explaining a rule of how the task should be done, but this rule is objectively wrong

behavioral and cognitive events. The final categories used were inspired partially by previous work, especially the predictions of the deliberate practice theory, and in part by what could be encoded reliably from the data. The coding manual is available on our website.

2.6. Interviews

The interview method was inspired by the retrospective interview introduced by Côté et al. (2005). The participants were asked to draw a timeline and list their phones in chronological order. They were then interviewed about their interactions and activities with these phones other than the call and SMS features. They then had to recall instances in which they had used specific features of smartphones (e.g., browsing or using Bluetooth). They were prompted to describe in detail each of these situations: "Can you describe the situation?" "Was it easy or problematic (if so, why) to execute the function?" "How did you learn about the function?"

After this, they were asked to recall and describe, (a) situations in which they had learned a significant amount about their phone, (b) when they had encountered particularly difficult situations with their phone, (c) particularly unpleasant situations, and (d) reading information and texts about their phone. Finally, they were asked whether they had studied or learned about cell phones in any way not previously mentioned during the interview.

The interview was semi-structured. The dialogue was allowed to flow freely when relevant and illustrative discussion occurred. An interview lasted about an hour.

3. Results

We first analyze task performance in terms of success in the task (Section 3.1.) and completion times (Section 3.2.), after which we turn to differences in solution strategies (Section 3.3). Section 3.4 reports findings from the analysis of verbal protocols and Section 3.5 from the interviews. An alpha-value of 0.05 is used for significance testing, unless otherwise specified.

3.1. Task success

The novices were the least successful in accomplishing the tasks, while the experts were the most successful, as shown in Fig. 3. Experts completed all tasks with only one exception, namely one expert did not find a free game on the Internet. Most of the casual users failed the task of installing a game on the smartphone and some were not able to complete a few of the other tasks: two failed in sending a file via Bluetooth in the file transfer task and one failed in shooting a video and in downloading one. All novices failed in downloading a game and four out of 10 failed in at least one other task.

A one-way ANOVA showed significant differences between the groups, $F(2,23) = 3.8, p = .039$. Post-hoc tests with Tukey's HSD showed a significant difference only between the two extremes; in other words, between the novices ($M = 5.40$, 95% *CI* 4.71–6.09) and the experts ($M = 6.75$, 95% *CI* 5.95–7.00), $p = .035$.

3.2. Task completion times

Mean task completion times in the seven tasks are presented in Table 4. Overall, there were statistically significant differences between novices and the two experienced groups but no reliable differences between experts and casual users. The novices were slowest in all tasks except the View video task where their performance did not differ significantly from the two other groups. Averaging over all tasks, the novices spent more than twice as much time on the tasks as the casual users and were more than triple the experts time. This effect is highly significant (both p's ≤ 0.001, see Table 4).

Note that the means in Table 4 were restricted to times for successfully completed tasks. In a supplementary analysis incorrect solutions were assigned the longest actual completion times (per task), but this analysis did not lead to different conclusions. Secondly, we examined the homoscedasticity assumption with Levene's test and found that the assumption was violated in all task conditions, save the View video task where no difference was found. We therefore performed statistical testing after giving the completion times a logarithmic transformation, as recommended by Winer et al. (1991). Post-hoc testing with log-transformed data attenuated the group difference, but the level of significance was only changed for Task 1 (N vs. E: $p = 0.033$) and Task 3 (N vs. E: $p = 0.001$; N vs. C: $p = 0.001$).

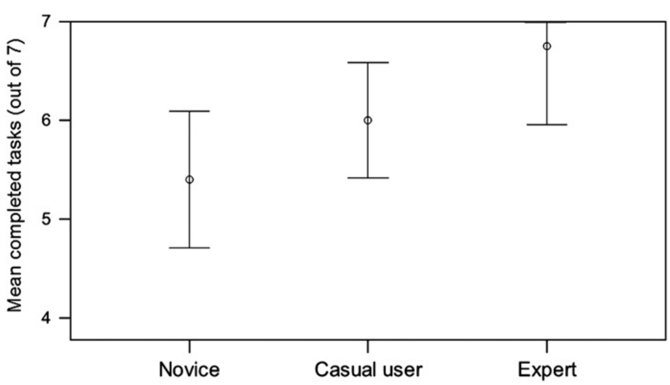

Fig. 3. Number of correctly solved problems for each of three user groups. Experts were significantly better than novices. Vertical bars denote 95% confidence intervals.

Finally, we examined the effect of self-reported familiarity among novices and casual users (all experts had done all the tasks previously) on task completion times, but only one borderline-significant effect was found, particularly for the file transfer task (among casual users, $p = 0.066$).

3.3. Task solution strategies

The proportions of categorized actions are presented in Table 5. Because of low frequency of some of the categories, statistical testing was performed on two super categories: *useful actions* and *non-useful actions*. As Table 5 shows, neither useful action nor non-useful actions show significant differences between groups. However, the *proportions* of useful actions (out of all actions) were vastly different. More than half of the novices' actions were non-useful, whereas the casual users and the experts had proportionately less non-useful actions (Table 5).

In the following section we evaluate qualitative observations for each individual task.

Table 5
Actions taken during task performance.

Action	Novice	Casual user	Expert	F	η^2	p
Directly useful action %	47.6	79.1	87.3			
Shortcut %	0	0.9	0.9			
Mean useful actions	14.4	17.3	21.3	1.954	0.187	0.17
Physical exploration %	4.9	0.5	0.9			
Accidental button press %	1.4	0.3	0			
Wrong button chosen %	4.8	0	0			
Wrong application/folder %	40.6	18.1	9.6			
Unnecessary subtask %	0.7	1.1	1.2			
Mean non-useful actions	19.0	9.0	3.5	3.177	0.272	0.07
Mean proportion of useful actions of all actions %	48.3	74.6	86.1	7.099	0.675	0.006
All actions %	100	100	100			

Table 4
Mean task completion times (s) by user group with 95% confidence intervals in parentheses.

	Group			*p*-values of post-hoc comparisons[b]	
Task	(N)ovices	(C)asual users	(E)xperts	*N* vs. *C*	*N* vs. *E*
(1) WiFi connection	230 (139–322)	90 (51–130)	89 (8–188)	0.041	0.057
(2) Calendar entry	108 (72–143)	46 (29–62)	36 (23–49)	0.003	0.008
(3) Video capture	208 (73–317)	42 (−2–87)	18 (13–22)	0.021	0.037
(4) File transfer	269 (131–406)	190 (114–265)	75 (27–122)	0.410	0.045
(5) Game install	–	335	491	–	–
(6) View video	227 (140–314)	245 (166–325)	123 (38–208)	0.924	0.228
(7) Audio recording	279 (77–480)	58 (26–89)	24 (10–57)	0.015	0.030
Mean[a]	217 (155–279)	106 (83–129)	61 (40–81)	0.001	0.001

Note: No significant differences were found between C and E groups so the corresponding *p*-values are not reported.
[a]Game installation task not included in this mean.
[b]Tukey's HSD.

3.3.1. Task-specific differences

The task involving the WiFi/WLAN connection was easy for all but the novices. Given that this task was presented first, the novices used time during this task to familiarize themselves with the new phone. For example, some users tested whether or not the phone has a touchscreen. Many novices were not certain what WLAN meant; however, all of them associated it with the Internet.

The calendar entry task was the only task that was accomplished by every user. Novices were able to draw from their experience with calendar applications on other phones.

Finding the right button (on the side of the phone; Fig. 1) was problematic for the novice users in the video capture task. It was necessary to explore the sides of the phone, not just the front. Not realizing this, some novices used the secondary camera that could be activated with the center button. This task was easy for experts and casual users.

The task involving file transfer was challenging for many novices and casual users. Three casual users, two experts, and two novices established a protected link between phones, which was unnecessary. Thus, this was the only task for which some of the experts exhibited imperfect conceptual knowledge. Some users thought that they would have to know a password, the password could, however, be set by the user at any time.

The task involving downloading a game was not successfully completed by any of the novices nor the majority of casual users. One of the experts failed this task. The most difficult aspect of this task was to find a free or trial version of a game from the Internet by using the browser. As a consequence, the performance on this task may reflect skills browsing the internet to a higher degree than skills directly involving the smartphone.

The video task was easy for most users, even novices, because they had learned to use the browser in the previous task and therefore knew a website that provided videos.

In the audio recording task, roughly half of casual users and experts, and most novices, made mistakes while trying to locate the audio recorder in the application menu, which was behind two folders. Some users incorrectly thought the camera application or music player could perform the action, which led to ineffective activities that did not directly contribute to the solution to the task.

3.4. Cognitive outcomes

Think-aloud data are presented in Table 6. To sum up the statistically significant differences, casual users and experts mostly verbalized their current actions "online" as they generated the solution to the task, whereas the novices reported more questions, uncertainty, and testing out of alternative actions. With a stricter, Bonferroni-adjusted criterion for the alpha-level (with 12 DV categories, the new alpha-level is 0.0042), testing, question, uncertainty, and total number of events continued to show significant differences among the groups. Moreover, we did log-transformations for all categories where the homescedasticity assumption was rejected by a significant Levene's test. This transformation attenuated the results, but did not change the pattern of statistical significance from the original Bonferroni adjusted tests.

The verbalizations of the novices contained significantly more questions and tests of alternative options than casual users and experts did. The verbalizations of novices revealed uncertainty in the meaning of concepts and navigation routes in the user interface. Sometimes, concepts and routes were erroneously intertwined, but this trend was not significant. For example, Bluetooth functionality in the file transfer task was mistakenly associated with browsing, although the Bluetooth task does not demand a browser. Another example is that some novices considered and explored the camera functions when trying to find the audio recorder, although they are two unrelated applications in the interface. Furthermore, only novices made inferences based on the symbols presented in the interface, but this frequency is too low to reach statistical significance. The novices made inferences about pictures in the interface as exemplified by comments, such as "that camera must be for video shooting" or "that planet is the Internet."

Additionally, we observed that casual users and experts were more knowledgeable and familiar with the device's *physical* buttons and their functions. Given the novices' lack

Table 6
Analysis of think-aloud protocols in percentages and as comparisons of means.

Category	Novice	Casual user	Expert	F	η^2	p
Reporting action %	24.6	58.5	60.7			
Mean	13.9	17.5	17.0	1.164	0.461	0.332
Testing %	16.8	7.7	9.8			
Mean	9.5	2.3	2.8	8.99	0.100	0.002
Question %	26.9	9.7	7.1			
Mean	15.2	2.9	2.0	13.744	0.567	<0.001
Uncertainty %	26.5	14.4	7.1			
Mean	15.0	4.3	2.0	15.318	0.593	<0.001
Inferring UI %	1.6	0	0			
Mean	0.9	0	0	5.574	0.347	0.011
Technical explanation %	0	1.7	1.8			
Mean	0	0.5	0.5	1.332	0.113	2.85
Functionality %	0	1.0	1.8			
Mean	0	0.3	0.5	1.767	0.144	0.195
Anticipation %	0	1.7	2.7			
Mean	0	0.5	0.8	1.944	0.156	0.168
Confidence %	0.4	0.3	2.7			
mean	0.2	0.1	0.8	2.500	0.192	0.106
Recalling %	1.4	3.3	4.5			
mean	0.8	1.0	1.3	0.132	0.012	0.877
Other devices %	0.9	0.3	0			
mean	0.5	0.1	0	2.139	0.169	0.143
Wrong rule %	1.1	1.3	1.8			
mean	0.6	0.4	0.5	0.152	0.014	0.860
Total %	*100*	*100*	*100*			
mean	56.6	29.9	28.0	13.749	0.567	<0.001

of familiarity with the device it was sometimes necessary for them to explore the device by turning it around and studying its different sides. And one of the novices also tested whether it had a touchscreen. Some novices did not find the keyboard immediately and did not initially realize that it was hidden underneath the lid.

Overall, verbalization of *non-observable factors* affecting the smartphone's interface was only demonstrated by experienced users, and as expected not with novices, but the frequency of these verbalizations were too low to show significant differences among groups. Experts and casual users verbalized more explanations – for example, technical explanation as to why the smartphone was working slowly or otherwise imperfectly – and they were also able to point out functionalities that were specific to the type of phone they were using. Experts and casual users also explicitly stated accurate action plans and anticipated the resulting outcomes for the smartphone, whereas novices did not demonstrate this ability.

Attempts at inferring labels or options in a user interface were rare as well. Sometimes there were verbalized references to one's memory of previous instances. Novices made references to other devices, computers, and older cell phones, in order to understand what was to be done with the smartphone, but in general such remarks were rare and the differences were not significant. All groups made remarks reflecting their confidence, such as "this is easy," but only occasionally. There were no significant differences among the groups in these variables either.

Comparing the groups with a post-hoc test (Tukey's HSD), the think-aloud data did not reveal any statistically significant differences between casual users and experts, only between novices and the other groups.

3.5. Learning histories

Casual users' and experts' learning histories are described in Table 7 in terms of the features of deliberate practice.

Most casual users were found to engage in intense acquisition of knowledge of a given smartphone when they familiarized themselves with a newly acquired phone. Following this initial phase of familiarization casual users learn on an *ad hoc* basis, in response to specific situational needs. In contrast, experts' learning histories included more systematic and regular opportunities for learning. They reported regularly thinking about general problems with smartphones when helping clients. Experts described a systematic approach to problem-solving situations. For example, one expert mentioned his strategy of trying to reproduce the error message that the client had originally received. Another expert described a strategy of first determining whether the source of the error is in the software or in the physical device (phone).

Among casual users, no systematic structure of practice activities was reported. In contrast, experts described systematic learning patterns. Three of the four experts mentioned that functions of a new phone are systematically reviewed and browsed upon acquisition – for some of the experts in a particular order – while the fourth expert described a more relaxed and exploratory practice. Another common strategy involved checking out how a new phone differs from previous models from the same manufacturer. However, experts' learning was not designed or monitored by "teachers" or "coaches." Rather, learning was a more solitary activity involving self-regulated exploration and practice.

Different factors motivated learning about smartphones among the groups. All experts and some casual users expressed a general interest in technology, not just phones. The casual users reported that the acquisition of a new phone aroused interest in exploring it and learning to use it. Specific goals also motivated learning: a particular function of the device was studied because it was perceived as personally useful.

In addition to using and testing the device, external information sources were seen as means to learn the phone: the Internet, friends, help desks, manuals, and print media were mentioned. Googling and browsing forums were

Table 7
Learning histories of casual users vs. experts compared to deliberate practice theory. Qualities refer to definitions given in Table 1.

Characteristic	Casual users	Experts
1. Motivation	Some general interest in technology, enthusiasm for a new device, instrumental in problem situations	General interest in technology, but mostly work-based
2. Concentration	Problem situations demanding high concentration	Problem situations demanding high concentration
3. Design of practice	No specific design. Some manual-reading	Systematic focus on features of a device. Some courses offered by others
4. Feedback	Several external information sources. No teacher–student interaction	Several information sources. No teacher – student interaction. A few cases of trying to acquire feedback on success.
5. Regularity	Upon acquisition of a new device, *ad hoc* in problem situations	Upon acquisition of a new device. On a daily basis while helping customers
6. Emotions	Avoidance of problem situations that are not enjoyable	Problem situations that are hard and stressful, but no self-driven pursuit of hard challenges

mentioned as a common source of *solutions* to problems by several individuals among both casual users and experts. Friends and other people in general were also consulted to solve problems, and some casual users also regularly talked with friends about their phones. Finally, print media were mentioned as a source for providing information about new devices and their features.

Two casual users mentioned using manuals, while three users explicitly said that they would never read a manual. One expert mentioned that if he could not find every feature that he was supposed to find from examining the device, he might browse the manual. However, another expert also noted that it is impossible to learn every possible aspect of the phone and that understanding increases gradually on a case-by-case basis while helping clients.

Learning to use the phone was not always enjoyable and at times demanded high concentration. Differences in reported level of concentration and enjoyment were present but not a prominent aspect of smartphone use by the casual users. Experiences of unpleasant situations involving smartphone use were reported. However, in this group, we found no evidence in the interviews of users systematically seeking challenging situations just for the purpose of learning, or decisions to learn despite negative emotions.

During the performance of the tasks participants gave occasional evidence for high levels of concentration. This was particularly salient when the users encountered difficulties: the think-aloud protocols contained a small number of remarks that contained expressions of emotion, and thus were irrelevant to generating a solution to the task. Concentration was inferred from the participants' visual gaze being focused on the smartphone almost without interruption. These observations were consistent with their answers to questions given after the end of the task, such as "Did the task demand concentration?", where they reported a high level of concentration.

4. Discussion

In this study, three groups of smartphone users were compared: novices, casual users, and experts. There are four main findings:

1. *Practice and learning*: According to the interviews, casual users' learning occurs mainly during routine use with three prominent types of learning episodes: (1) familiarization with a new phone, (2) following media and WWW content concerning the phone, and (3) *ad hoc* problem-solving situations. Experts' learning is more regular as it occurs upon introduction of every new phone. It is also more systematic as there is goal-setting and exercises and it involves daily encounters with challenging problems. Successful operation of the device where the desired outcome and function can be readily demonstrated is easy to determine and hence there did not seem to be any need for any additional external feedback to evaluate the quality of developed solution methods.
2. *Task performance*: Experienced users (casual users and experts) were faster than novices in completing the tasks and more successful in completing the tasks. In our data, no significant differences were observed between casual users and experts.
3. *Optimality of solutions*: Analysis of solution paths suggests that novices carry out proportionately more actions that are unnecessary for completion of the assigned tasks, such as going to the wrong folder or executing the wrong command. Moreover, novices' thoughts reflect significantly more cases of testing of options than the experienced users and they asked significantly more questions to themselves and elicited more expressions of uncertainty.
4. *Representation of the problem*: Overall, during the performance of the representative tasks in our study, the participants rarely verbalized thoughts reflecting conceptual changes, anticipation of upcoming displays of information, inferences based on experience and knowledge of other devices, and explicit recall of previous experiences of similar tasks. Casual users' and experts' performances did not differ significantly from each other, nor did their think-aloud protocols and associated encodings of events show consistent differences.

4.1. Appraisal of results: a device-specific skill

The significant differences in performance between casual users and novices imply the existence of a *device-specific* skill. Given that casual users and novices were matched on their *domain-general* skills, the inferior performance of the novices must be accounted for by their lack of device-specific experience. The novices needed more than twice the amount of time to complete the tasks compared to the other two groups of more experienced users. Given that experts were close to ceiling in task success rate and faster in task completion times, the difference cannot be explained away by means of speed-accuracy trade-off. This difference in completion time between experienced and inexperienced users may have real-world implications for whether someone would be motivated to learn the phone adequately. Only further research would allow us to know how much and what type of experience an inexperienced novice would need to be able to attain the speed of performance of a casual user. Our current findings cannot assess the degree of transfer of the casual users to a different smartphone model and whether their performance on representative tasks with that phone would have been significantly superior to the performance of the novices in the current study. The extent to which the superior performance of the casual users is due to the actual model of the phone vs. smartphones in general is a topic for future studies.

The superior performance of casual users over novices was linked to their interactions with their smartphone. While casual users' practice activities are less regular, less extensive, and less systematic than the experts', they still require a clear investment of their time. Casual users' learning perhaps could be characterized by Simon's (1956) concept of *satisficing*: they invest in learning activities only as much as necessary to achieve a satisfactory level of performance, but not more. Satisficing is visible in their familiarization with a new phone that is more exploratory and opportunistic than experts', who go through different features of a new phone and even take pains to find out why some features are missing. A related aspect that caught our attention is the social nature of casual users' methods for addressing encountered problems that they are unable to readily solve. Our interviews show that the main methods of solving problems with smartphones involve, even among experts, searching the Internet, especially its forums, and talking to other users.

Our interviews revealed that casual users do not seek challenges to improve their mastery; in contrast, they actively avoid frustrating situations. It is an interesting question for further study how far users get in this skill range solely on the basis of familiarization with a new phone and how much of their learning takes place after that initial familiarization due to exposure of external information and in *ad hoc* problem-solving. Perhaps *guided* familiarization that takes the user through the displays and concepts of a new phone could be developed, possibly "jumpstarting" more proficient use of the device.

To our surprise, we found that the skill of casual users is less conceptual than some other domains of computer skill, such as problem-solving with search engines (e.g., van Braak, 2004). We are not aware of any evidence that even experts would exhibit superior conceptual knowledge in representative tasks of smartphone use, even though some of these tasks involve manipulating a complex technical apparatus such as the Bluetooth.

Instead, the generation of task solutions turned out to be more stimulus-driven than we had expected. This perceptual influence impacts the structure of skills sufficient to successfully guide the user toward the desired goals. As stated above, there was very little evidence for planning/recall or anticipation/inference in casual users' think aloud protocols given during the performance of the tasks. Instead, interactive goal-pursuits with the mobile devices we studied are characterized as rapidly executed series of scans and selections within a list of candidate items on a user interface. This is somewhat akin to the TOTE model (test–operate–test–exit; Miller et al., 1960). When working with a smartphone, each decision point involves a choice from a small set of options—most of which are visually available on the screen. Under these conditions decision options can be scanned quickly for familiar or directly recognizable items. The cost of trying out an option is small. The new display that results from the selection can also be quite quickly scanned to assess whether the choice was good. If it was not, one can use the "back" button or, for the minority of displays that did not have such a button, the application can be restarted. This low cost of trying out an option may explain the absence of deliberate efforts to understand the interface that we observed in experienced users' interaction. By contrast, a novice's main hurdle involves testing options to find a stepping stone toward their desired outcome, and they may have to do this testing several times per display.

Further research is needed to determine *why* experienced users are able to navigate the displays more quickly. A likely hypothesis might involve quicker and more selective recognition of good options. On the basis of a feeling of familiarity with an interface element, experienced users may be able to identify the next action more efficiently. When none of the candidate actions on a display look promising at a quick glance, previous experience with options helps one narrow down the list of candidates. This explanation is in line with a recent predictive model (Cockburn et al., 2007), according to which practice improves menu selection performance by modifying two processes: 1) decision/search time among visible list of candidates and 2) target acquisition time. The former is a linear function of the number of items and information theoretical content (entropy) of the items, and therefore modeled with the Hick–Hyman law. The latter is a function of the target size and distance and modeled with the Fitts' law (for explanation of the two laws, see Seow, 2005). In their model (Cockburn et al., 2007), both components are differentially affected by what the authors call "expertise" (operationalized in that study as number of trials in an experiment): with an increasing number of trials, menu performance improves but it becomes proportionately less dominated by visual search and more by decision among the items. Experienced users may also be able to execute longer chains of commands from memory, effectively navigating via familiar "paths" through the displays, while a novice has to deal with each display separately.

4.2. Opportunities for improving the method

Although the experts' learning histories were more consistent with the engagement in deliberate practice than the learning methods of the casual users, the experts were not able to reliably outperform the casual users in these everyday tasks. Although the average task success and associated completion times were numerically superior for the experts, the two groups did not differ significantly from each other. There are three possible explanations for this lack of significant differences that suggest improvements in future studies.

First, the number of tested experts was small. However, in multi-group studies of expertise, a small N for the top-level group is not unusual. The increasing trend (non-significant) suggests that with a larger group of expert users, the differences in performance between experts and casual users could become statistically significant, although the effect size would not be large.

Second, our tasks were created to be a sample of representative and frequent tasks of smartphone use. With a larger collection of tasks that included less frequently used applications, one can expect skill differences to emerge between casual users and experts.

Third, and most pertinent, there were large individual differences among the four professionals. These experts were identified using *social* criteria, because there are no external criteria for this domain akin to the ELO rating in chess (Elo, 1978) based on many chess matches in tournaments (for an extended discussion of social vs. performance criteria for selection of experts, see Ericsson, 2006b, 2009). Two of the experts trained other help desk personnel, and one of them had been recognized as his organization for being "best with mobile phones." The two other experts exhibited less systematic learning practices, with one expert performing the experimental tasks close to the performance level of the casual users. In future studies, we recommend paying closer attention to criteria such as who solves the most important problems, who teaches others, to whom other experts turn to when having problems.

5. Conclusion

With the emergence of the World Wide Web in the mid-1990s, followed by mobile devices in the late 1990s, and more recently laptops and smartphones we perceive a new empirical phenomenon involving acquisition of skills: most users do not have professional backgrounds, and they have limited education in computer use and hardly any motivation to study computers. As users become increasingly dependent on these devices, the issue of skill acquisition is increasingly important for manufacturers and the society as whole.

An interesting question concerns the relation between the design of everyday technology and necessary and appropriate levels of skill handling the devices. In our study, we have already discussed some possible methodological issues leading to the lack of significant differences between professional and casual users. It is, however, possible that the small differences may have been due to the user interface design, which limits the performance benefits achievable by a superior deep understanding of the device. In other words, there may not be enough "room" for large individual differences to emerge in this domain. There may simply be very little advantage for conceptual understanding or "intermediate layers of knowledge" to appear in an interaction paradigm where goal-pursuits take place by repeated choice from small sets of options. Designers strive to develop an "easy-to-use" device that can be mastered will minimal experience for quick adoption and utilization and thus need not require a deep understanding. Efforts to attain a deep understanding of its internal structure may even be discouraged by means of the current designs. Consistent with this argument, even our best experts with the studied mobile phone exhibited non-optimal solution paths and there were a few instances of imperfect conceptual knowledge of technical concepts (e.g., regarding Bluetooth).

How should everyday technology be designed to maximize scope and efficiency of use with a device while minimizing skill acquisition and errors during initial mastery? As the manufacturers keep producing more advanced versions of their products, does it make sense to become an expert on these phones when there is a better version available in six months? Maybe the best strategy in this situation is to support skill that allows one to easily transition to the new models. Therefore, we see that it is critically important that we develop objective measurement of this type of performance along with its structure and acquisition so we can optimize the benefits of informal learning and user interface design as mediators of improved performance.

For designers, we raise the issue that already acquired skill and cognitive models of a device should be considered as part of users' long-term experience of a product, or "user experience" (Hassenzahl and Tractinsky, 2006). With the emergence of increasingly complex devices there is not only an increase in experiences of past devices and expectations about new functions (Petersen et al., 2002), but also in the skills required to use them efficiently. The present study outlines a methodology for tracing the type and amount of learning activity of casual users and the structure of their acquired skills in executing representative tasks. In the future, this method could be combined with diary and traces of past interactions with the device to describe the acquisition of skilled performance as a function of user experience over time. For example, does most effective learning take place through modeling of peers, external sources, expert advice, trial and error, or self-regulated learning? This information would permit designers and users of devices to assess, not just the cost and functionality of the device, but also the predicted investment in time to attain a certain level of mastery along with a specified level of expected efficiency in using the device and the time required to acquire updated skills for future versions of the same type of device. Until we can describe how skillful use of smartphones are effectively attained by different types of users and subsequently transferred to newer and more advanced devices we will not be able to help designers make judgments and trade-offs concerning the development of new technology and interfaces.

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Appendix A

See Table A1.

Table A1
Examples of direct routes to task completion.

WiFi Connection	**Calendar entry**	**Video capture**	**File transfer**	**Game install**	**View video**	**Audio recording**
Front screen	Front screen	Front screen	Front screen	Front screen	Front screen	Front screen
↓	↓	↓	↓	↓	↓	↓
Choose “WLAN scanning”	Choose calendar	Open camera lens	Press menu button	Press menu button	Choose Internet	Press menu button
↓	↓	↓	↓	↓	↓	↓
Choose “Search for WLAN”	Press right	Press up	Press center button: “gallery”	Choose “Applications”	Press center button (select access point)	Choose “applications”
↓	↓	↓	↓	↓	↓	↓
Select a network	Press center button	Press center button: “video mode”	Press center button: “images & videos”	Choose “N-Gage”	Type video service webpage (e.g. YouTube)	Choose “media”
	↓	↓	↓	↓	↓	↓
	Press center button: “new entry”	Press camera launch button	Press options button	Choose “Showroom”	Play video	Choose “recorder”
	↓		↓	↓		↓
	Press center button: “meeting”		Press center button: “send”	Choose e.g. “game of the week”		Press center button: “recording”
	↓		↓	↓		
	Write meeting details		Choose “Via Bluetooth”	Press center button (select access point)		
			↓	↓		
			Press “yes”	Press “yes”		
			↓			
			Press center button: “search devices”			
			↓			
			Choose “stop”			
			↓			
			Choose researcher’s mobile phone			

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