

Modeling Interruption and Resumption in a Smartphone Task:

An ACT-R approach

Maria Wirzberger, Nele Russwinkel

Technical University Berlin, Berlin, Germany

Abstract: This research aims to inspect human cognition when being interrupted while performing a smartphone task with **three levels** (no, low, high) of mental demand. Due to its benefits, especially in the early stages of interface development, a cognitive modeling approach is used. It applies the cognitive architecture ACT-R to explain the task-related cognitive processing.

The inspected task setting involves a shopping scenario, dealing with interruption via product advertisements and mental demands by the respective number of people shopping is done for.

Model predictions are validated through a corresponding experimental setting with 62 human participants. Comparing model and human data in a defined set of **performance-related parameters** (in 2.2–3), four parameters) displays mixed results that indicate an acceptable fit.

Finally, potential explanations for the observed differences are discussed at the end.

Keywords: ACT-R, Cognitive Modeling, Interruption, Mobile Interaction

1 Introduction

1) According to statistical information, more than two billion people worldwide use a smartphone. Despite their great convenience in daily use, interruption is a frequently occurring phenomenon when interacting with such devices.

2) Smartphone use is embedded into various situational environments. If a user is interrupted during periods with already increased mental demands, they might put additional limits on the available cognitive capacity.

To avoid or at least moderate the resulting impairment, there may be great value in considering task-related cognition when developing and designing such interfaces.

3) The existing research inspects how a certain kind of interruption affects human cognition while performing a smartphone task. Due to the mentioned use scenario, various levels of mental demand are considered.

1.1 Matter of Interruption

1) **Interruption** as a human experience is usually neither planned nor expected, but a cognitive interruption to the task being performed at the time. It can be induced by

internal or external sources, resides within a given situational context and indicates a delay in finishing the previous activity.

Interruption is known to impair the main task performance due to a set of disruptive factors, including factors that are very similar to the main task, factors that occur immediately, or lack of opportunity to refuse or delay the interruption.

Resumption refers to the main goal after facing an interruption involves successfully returning the mental resources to the actual focus of attention.

2) Altmann, Trafton and colleagues described cognitive processes in the face of external interruptions. They assume *a time course model* of interruption and resumption: After starting a main task and performing it for some time, an alert appears announcing the interruption before it actually occurs.

Interruption lag refers to the time span between the alert and an upcoming interruption, and it is supposed to prepare for an effective return to the main task.

Resumption lag is the time interval between ending the interruption and successfully resuming the main task, and it is a true measure of the extent of disruptiveness.

1.2 Resource Limitation

1) When dealing with interruptions, the limitation of working memory in time and capacity is an important restricted resource.

The first is that information in working memory decays over time. To extend time available, people can rehearse relevant information.

In contrast, the matter of capacity indicates that just a defined amount of information can be held active at the same time. It should be between five and nine items, although more recent research proposes smaller numbers.

2) In general, when performing a memory-related task, memory load must be maintained by working memory. Increasing such load might affect task performance, making it difficult to retrieve necessary information.

2 Methods

2.1 Cognitive Modeling Approach

1) In the field of human-computer interaction, applying cognitive user models is gaining more and more attention. So far, the Lisp-based cognitive architecture ACT-R has been used actively to address a variety of basic and applied subjects. Figure 1 gives an overview of the standard modules contained in the current ACT-R distribution. Each module holds a buffer, serving as an interface to support communication between modules.

2) Information is processed within the outlined structure via chunks, i.e. small units

encode knowledge elements related to a certain category (chunk-type) and containing specific attributes (slots). Although processes in different modules can be executed in parallel, each buffer can hold just one chunk at the same time, representing the existing limitations in information processing resources.

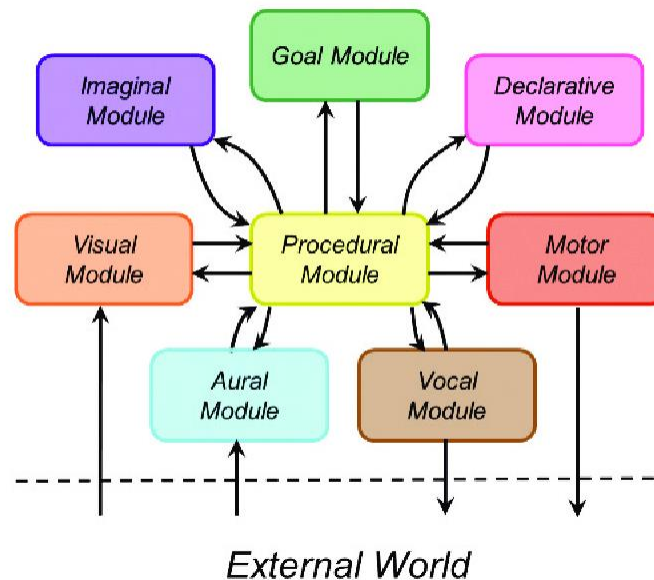


Figure 1: Overview of modules contained in ACT-R 6.0. Adapted from [5] and [2].

2.2 Inspected Task Setting

1) Shopping list application:

To examine cognitive processes of an interrupted task, a shopping scenario was used in this project. It operated on a simple smartphone shopping list application, as shown in Figure 2, and consisted of coding, remembering, searching and selecting a set of 12 predefined products, equally distributed within three runs. (That means, it will run three times, each time has 4 products.)

2) Task setting

At the beginning of each run, products appeared in a fixed sequence listed on the screen. At the end of the task, all products still remembered from the whole selection part had to be recalled.

During two of the three runs, interruptions in terms of product advertisements occurred with varying frequency. They always announce special offers in connection with the previously selected shop. The advertisements are triggered after a certain number of products are successfully selected. In order to end the interruption and return to the product selection, a decision for or against the offered product was forced. In conditions with enhanced mental demands, shopping was done for three different

people. Therefore, additional information about whom the product should be bought for had to be remembered and recalled throughout the task as well.

3) Behavioral performance parameters of task-related cognition:

a) Product selection time: it was computed as the time difference between successfully selecting a product and returning to the related shop menu.

b) The number of selected products: it was the correctly selected products calculated for per run.

c) Resumption time: it included the difference between the offset of the interruption and the transition back to the shop menu.

d) Final recall performance: it was assessed by summing up correctly recalled products after finishing the selection part.

2.3 Creating the Model

1) Based on relevant literature, an ACT-R model was established. Key features of the described shopping list application were implemented in the ACT-R experimental GUI in a simplified way.

No alert was included, resulting in the absence of an interruption lag. Without this time span, there was no opportunity to explicitly create environmental cues or apply rehearsal before turning to the interrupting task. Therefore, naturally existing cues from memory or environment had to be used for resumption. For example, the memorized selection content or visible selection marks.

2) Model task:

The modeled task always started by reading the written product list and remembering its content. Then select the products during the navigation and selection procedure spanning the three menus, as shown in Figure 2.

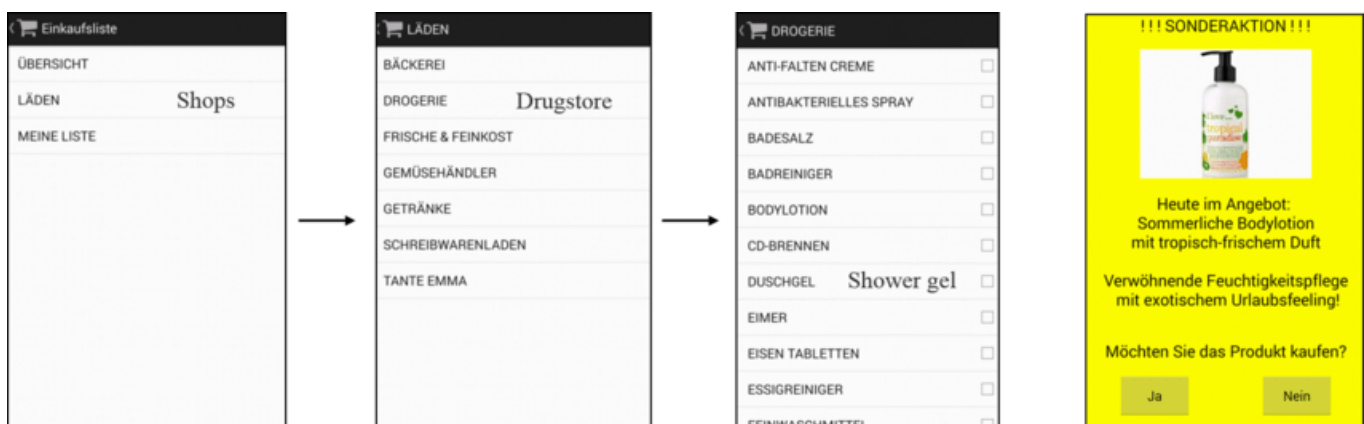


Figure 2: Main menu, store menu, example product menu for drugstore and example product advertisement for “body lotion” within the shopping list application.

*** Flow chart:**

- a) In case an **interruption occurred**, its message was read and a random decision for or against the offered product was made.
- b) By performing either a memory retrieval of the previously selected product or looking for a relevant environmental cue, i.e. a **selection mark** linked to the lastly selected product, **resumption started**.
- c) A retrieval of the selection history, i.e. products were selected at run time and previously stored in the intermediate memory. This is reminiscent of the recently reported **“the memory-for-problem-states theory”**.
- d) The next product was then searched for or the run ended when the reconstruction of the previous selection failed. If all four products were successfully selected or the next product was not retrieved, a run ended.
- e) After completing the third and last run, **the final product recall occurred**. Under conditions of enhanced memory demands, the product-related person had to be remembered throughout the task and recalled at the end as well.

2.4 Experimental Validation

- 1) To assess the adequacy of the cognitive user model in terms of human behavior, an experimental validation was conducted. 62 participants aged 20 to 49 years performed the described task using a LG Google Nexus 4 smartphone and Android serving as operating system.
- 2) A shopping scenario was created to foster the participant’s involvement in the task. It asked them to imagine being a virtual character, shopping with the app in their daily life. Under the memory enhancing condition, two characters were introduced, an old neighbor and a sick friend. Participants were provided with information about two people’s attributes and habits and their relationship to the participants.

3 Results**3.1 Model Behavior**

Looking at the resulting model behavior, when there were interruptions, fewer recalled products were shown and product selection took a little longer. As can be seen in Table 1, such effects showed up especially with increasing frequency of interruption. Moreover, the model performed better on all performance-related parameters without enhanced memory demands.

3.2 Model Comparison

- 1) Based on the examined model behavior, task performance was decline with increasing interruption and mental demands in human data. Descriptive values are shown in Table 2, statistical effects of differences in interruption and mental demands

were examined by computing the analyses of variance (ANOVAs) of product selection time, selected products and resumption time or a χ^2 -test of final recall performance.

2) In summary, none of the ANOVAs achieved significant results, neither for interruption nor mental demands. In contrast, a significant difference between high and low mental demands in the case of final recall showed up, $\chi^2 (15, N = 62) = 25.397$, $p = .045$, supporting the assumption of worse final recall performance when mental demands are enhanced.

For purposes of model comparison, human and model data points for high and low mental demands respectively, were compared by visual and numerical means. as shown in Table 1 and Table 2.

Table 1: Descriptive values of the **model behavior** regarding the inspected performance parameters.

| | Mental demands | No ad | | Low ad | | High ad | | Overall | |
|---------------------------------|----------------|-------|------|--------|------|---------|------|---------|------|
| | | M | SD | M | SD | M | SD | M | SD |
| Product selection time (in sec) | H | 7.42 | 0.64 | 7.31 | 0.73 | 7.58 | 0.77 | 7.41 | 0.28 |
| | L | 6.09 | 0.64 | 6.09 | 0.69 | 6.10 | 0.72 | 6.05 | 0.20 |
| | – | 6.76 | 0.93 | 6.70 | 0.94 | 6.84 | 1.05 | 6.73 | 0.73 |
| Selected products (sum) | H | 3.67 | 0.48 | 3.03 | 0.18 | 3.00 | 0.00 | 9.70 | 0.47 |
| | L | 4.00 | 0.00 | 3.77 | 0.43 | 3.30 | 0.47 | 11.07 | 0.52 |
| | – | 3.83 | 0.38 | 3.40 | 0.49 | 3.15 | 0.36 | 10.38 | 0.85 |
| Resumption time (in sec) | H | | | 3.08 | 0.68 | 3.95 | 0.36 | 3.66 | 0.29 |
| | L | | | 2.65 | 0.27 | 2.72 | 0.26 | 2.69 | 0.20 |
| | – | | | 2.86 | 0.56 | 3.33 | 0.69 | 3.18 | 0.54 |
| Final recall (in %) | H | | | | | | | 60.56 | 9.01 |
| | L | | | | | | | 84.17 | 6.32 |

Note. H: mental demands enhanced (data based on $n = 30$ model runs)

L: mental demands not enhanced (data based on $n = 30$ model runs)

–: no separation by mental demands (data based on $N = 60$ model runs).

Table 2: Descriptive values of the **human data** regarding the inspected performance parameters.

| | Mental demands | No ad | | | Low ad | | | High ad | | | Overall | | |
|---------------------------------|----------------|-------|------|------|--------|------|------|---------|-------|------|---------|-------|-------|
| | | N | M | SD | N | M | SD | N | M | SD | N | M | SD |
| Product selection time (in sec) | H | 31 | 9.32 | 5.72 | 31 | 9.58 | 5.89 | 31 | 10.07 | 7.44 | 31 | 9.61 | 4.63 |
| | L | 31 | 9.28 | 4.35 | 31 | 8.55 | 3.79 | 31 | 9.71 | 8.68 | 31 | 9.21 | 4.39 |
| | – | 62 | 9.30 | 5.04 | 62 | 9.06 | 4.94 | 62 | 9.89 | 8.02 | 62 | 9.41 | 4.48 |
| Selected products (sum) | H | 31 | 3.81 | 0.48 | 31 | 3.81 | 0.48 | 31 | 3.77 | 0.50 | 31 | 11.39 | 0.88 |
| | L | 31 | 3.90 | 0.30 | 31 | 3.77 | 0.50 | 31 | 3.81 | 0.48 | 31 | 11.48 | 0.85 |
| | – | 62 | 3.85 | 0.40 | 62 | 3.79 | 0.48 | 62 | 3.79 | 0.48 | 62 | 11.44 | 0.86 |
| Resumption time (in sec) | H | | | | 26 | 3.45 | 2.63 | 26 | 4.26 | 2.35 | 29 | 3.88 | 1.83 |
| | L | | | | 28 | 4.41 | 3.20 | 28 | 4.30 | 3.18 | 31 | 4.47 | 2.79 |
| | – | | | | 54 | 3.95 | 2.95 | 54 | 4.28 | 2.79 | 60 | 4.19 | 2.37 |
| Final recall (in %) | H | | | | | | | | | | 31 | 51.01 | 25.01 |
| | L | | | | | | | | | | 31 | 73.59 | 14.50 |

Note. H: mental demands enhanced, L: mental demands not enhanced, –: no separation by mental demands. Differences in reported subsample sizes result due to missing values.

3) Graphic Comparison, as shown in Figure 3 and Figure 4

Obviously, apart from the number of selected products, human data remain on a continuously higher level for all displayed parameters, indicating the model performed better than the human sample.

a) *Product selection time*, in the case of enhanced mental demands, model and human data point towards a similar direction, slightly increasing with enhanced frequency of interruption. In conditions with low mental demands, model data form a nearly straight line but human data show a considerable difference with increasing interruption frequency.

b) *The number of selected products*, human data stay almost at the same level across interruption frequencies for two mental demands. But model data perform differently. It is decrease with increasing interruption frequency for high mental demands.

c) *Resumption time*, there is a high similarity between model and human data for both levels of mental demand, although deviation between two datasets is slightly higher under low mental demands.

d) *Final recall performance*, the model performs better in both conditions, but model and human data show a similar trend with a higher number of recalled products under low mental demands.

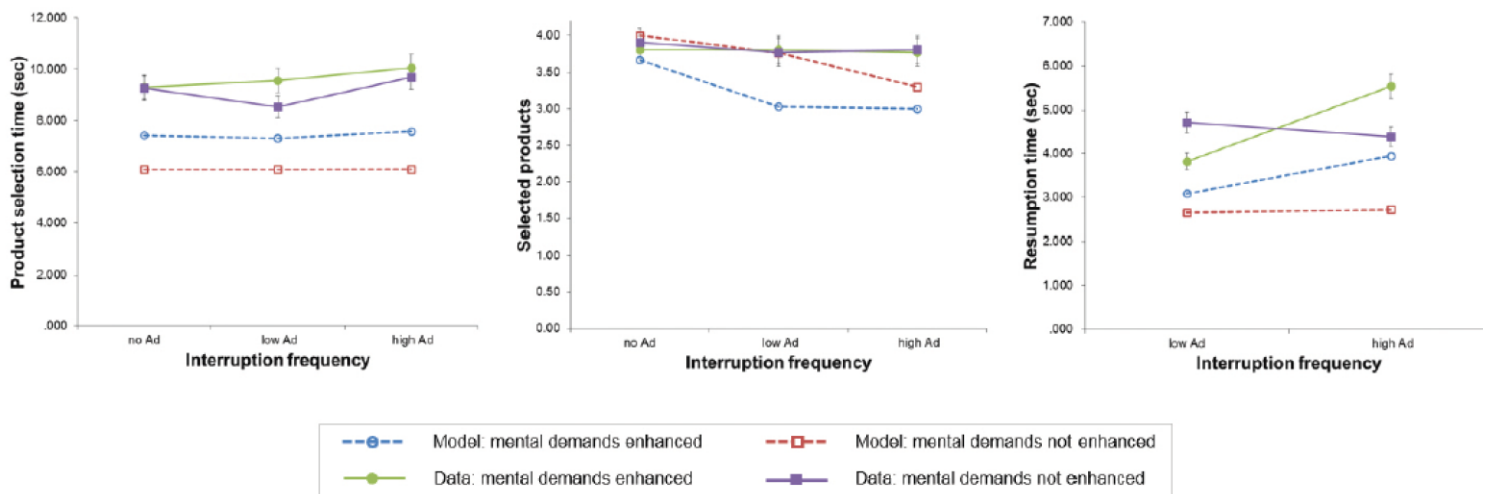


Figure 3: Comparison of model and human data concerning time, products and resumption. Error bars represent 95 % confidence intervals on human data.

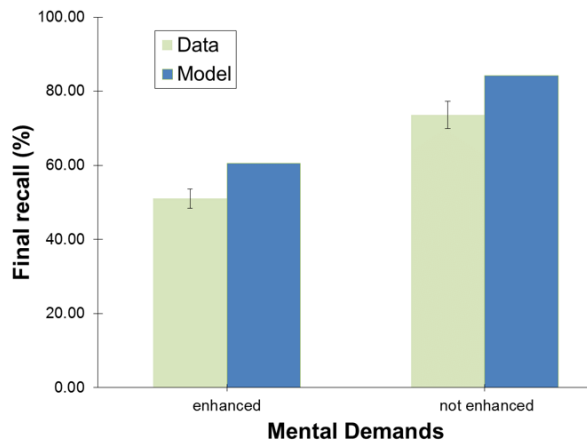


Figure 4: Comparison of model and human data concerning final recall. Error bars represent 95 % confidence intervals on human data.

Table 3: Differences in exact locations between model and human data points.

| | RMSD | |
|--|---------------------|--------------------|
| | High mental demands | Low mental demands |
| Product selection time (maximum: 10.07 sec) | 2.230 sec | 3.125 sec |
| Selected products (range: 0–4 products) | 0.637 products | 0.298 products |
| Resumption time (maximum: 4.41 sec) | 0.343 sec | 1.675 sec |
| Final recall (range: 0–100%) | 10.076 % | |

4) Numerical Comparisons in RMSD

It assesses the mean deviation between model and human data points regarding their exact location in units of the respective scale. Taking into account the scale's extremities, smaller values indicate less distance between both datasets, i.e. point to a better fit.

Results of the comparison, separated by the level of mental demands, are shown in Table 3. For example, in terms of resumption time under high mental demands, model and human data are located quite close together, whereas in terms of final recall, deviation is quite substantial.

4 Discussion

1) This research aimed to examine the effects of interruption and increased mental demands on human cognition in a smartphone task by applying a cognitive user model. The expected decrease included in the model could be confirmed experimentally in particular for the number of final recalled products.

2) The used interruption could have lacked disruptiveness due to its **short duration and familiar content**. Indeed, more than 80 % of the tested participants reported being familiar with smartphone use and for this reason may deal with interrupting advertisements on a regular basis. Because of its shortness, the interruption may have not been able to prevent people from rehearsing the content of the product list during its appearance.

Moreover, participants conducted the task at their own pace, potentially resulting in the performance of short cognitive breaks to create selective mental cues before

actually reading the advertisement. To achieve stronger disruption effects, it could be possible to increase disruptiveness by extending the duration or the amount of cognitive demands needed to deal with the interruption.

3) There are various opportunities to extend the computational model in order to enhance proximity to the obtained human data. A next step might comprise adjusting and / or including parameters that affect chunk activation and retrieval to achieve a more lifelike memory performance.

Furthermore, in the longer run, further elaborated features like individual differences in working memory or strategies and heuristics of decision-making when facing an interruption might represent valuable extensions.

In conclusion, the obtained results can definitely be taken as a cue for the benefit of using such an approach to predict and explain task-related cognitive processing in the given context. In particular due to their value in being applied at an early stage, they provide valuable input for developers and designers in creating interfaces able to actively support users when being interrupted.

References

- [1] Altmann, E. M., & Trafton, J. G. (2002). Memory for goals: an activation-based model, *Cognitive Science*, 26, 39–83.
- [2] Anderson, J. R. (2007). *How can the human mind occur in the physical universe?* New York: Oxford University Press.
- [3] Anderson, J. R., & Lebiere, C. (1998). *The atomic components of thought*. Mahwah, NJ: Erlbaum.
- [4] Anderson, J. R., Reder, L. M., & Lebiere, C. (1996). Working memory: Activation limitations on retrieval, *Cognitive Psychology*, 30, 221–256.
- [5] Borst, J. P., & Anderson, J. R. (2015). Using the ACT-R Cognitive Architecture in combination with fMRI data. In B. U. Forstmann, & E.-J. Wagenmakers (Eds.), *An Introduction to Model-Based Cognitive Neuroscience* (pp. 339–352). New York: Springer Science + Business Media.
- [6] Borst, J. P., Taatgen, N. A., & van Rijn, H. (2015). What makes interruptions disruptive? A process-model account of the effects of the problem state bottleneck on task interruption and resumption. In *Proceedings of the CHI 2015, April 18–23 2015*. Seoul, Republic of Korea: ACM Press.
- [7] Brixey, J. J., Robinson, D. J., Johnson, C. W., Johnson, T. R., Turley, J. P., & Zhang, J. (2007). A concept analysis of the phenomenon interruption. *Advances in Nursing Science*, 30(1), E26–E42.
- [8] Cowan, N. (2010). The magical mystery four: How is working memory capacity limited, and why?. *Current Directions in Psychological Science*, 19(1), 51–57.
- [9] Cowan, N., Morey, C. C., & Chen, Z. (in press). The legend of the magical number seven. In S. Della Sala (Ed.), *Tall tales about the brain: Things we think we know about the mind, but ain't so*. Oxford University Press.
- [10] Gillie, T., & Broadbent, D. E. (1989). What makes interruptions disruptive? A study of length, similarity, and complexity, *Psychological Research*, 50, 243–406.
- [11] Gray, W. D., Young, R. M., & Kirschenbaum, S. S. (1997). Introduction to this special issue on cognitive architectures and human-computer interaction. *Human-Computer Interaction*, 12, 301–309.
- [12] Marewski, J. N., & Mehlhorn, K. (2011). Using the ACT-R architecture to specify 39 quantitative process models of decision making. *Judgment and Decision Making*, 6, 439–519.
- [13] McFarlane, D. C., & Latorella, K. A. (2002). The scope and importance of human interruption in human-computer interaction design. *Human-Computer Interaction*, 17, 1–61.
- [14] Miller, G. A. (1956). The magical number seven plus or minus two: Some limits on our capacity for processing

information. *Psychological Review*, 63, 81–97.

[15] Prezenski, S., & Russwinkel, N. (2014). Combining cognitive ACT-R models with usability testing reveals users mental model while shopping with a smartphone application. *International Journal on Advances in Intelligent Systems*, 7(3–4), 700–715.

[16] Salvucci, D. D., & Taatgen, N. A. (2010). *The multitasking mind*. New York: Oxford University Press.

[17] Schunn, C. D., & Wallach, D. (2005). Evaluating goodness-of-fit in comparison of models to data. In W. Tack (Ed.), *Psychologie der Kognition: Reden und Vortraege anlaesslich der Emeritierung von Werner Tack* (pp. 115–154). Saarbruecken: University of Saarland Press.

[18] Statista (2015a). *Anzahl der Smartphone-Nutzer in Deutschland in den Jahren 2009 bis 2015 (in Millionen)* [Amount of smartphone users in Germany from 2009 to 2015 in millions]. Retrieved from <http://de.statista.com/statistik/daten/studie/198959/umfrage/anzahl-der-smartphonenuutzer-in-deutschland-seit-2010/> at June 17th, 2015.

[19] Statista (2015b). *Prognose zur Anzahl der Smartphone-Nutzer weltweit von 2012 bis 2018 (in Milliarden)* [Predicted amount of smartphone users worldwide from 2012 to 2018 in billions]. Retrieved from <http://de.statista.com/statistik/daten/studie/309656/umfrage/prognose-zur-anzahlder-smartphone-nutzer-weltweit/> at June 17th, 2015.

[20] Trafton, J. G., Altmann, E. M., Brock, D. P., & Mintz, F. E. (2003). Preparing to resume an interrupted task: Effects of prospective goal encoding and retrospective rehearsal. *International Journal of Human-Computer Studies*, 58, 583–603.

[21] Wickens, C. D., Hollands, J. G., Banbury, S., & Parasuraman, R. (2013). *Engineering psychology and human performance* (4th ed.). Upper Saddle River, New Jersey: Pearson Education.