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On the visual design of ERP systems – The role of information complexity, presentation and human factors

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Abstract

The investment in Enterprise resource planning (ERP) systems is indispensable for manufacturing companies to obtain competitive advantages in the globalized market. However, end-users are confronted with complex interfaces and poor usability of these systems. In the present multi-factorial experiment, we examined the effects of information complexity and presentation as a key aspect of usability with consideration of human factors on decision quality. By using alphanumeric tables of simulated ERP system data to make a decision, users' decision quality dropped with increasing information complexity and the use of a poor presentation. Furthermore, interactive effects of two different aspects of information complexity (data amount and task complexity) as well as compensatory effects through human factors were revealed. These findings show the importance of empirical user studies in this field and provide several practical implication. Especially, user-centered design processes can substantially contribute to a successful implementation of complex information systems, such as ERP systems.

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1. Background

Current production networks in globalized markets are characterized by increasing dynamic and complexity: Reduced time to markets, increasing product diversity, and increasingly complex multi-tier and world-spanning supply chains are faced with growing interconnectivity of production machinery, manufacturing execution systems, and enterprise resource planning systems under the label Industrial Internet, Internet of Things (IoT), or Industry 4.0. These trends offer great opportunities for increasing quality, quantity, and productivity, but also offer tremendous challenges. The Cluster of Excellence "Integrative Production Technologies for High Wage Countries" at RWTH Aachen University addresses these opportunities and challenges and aims at resolving the "polylemma of production" which spans along two dilemmas *plan-oriented vs. value-oriented production* and *scale vs. scope* [1]:

Planning-oriented approaches model production processes and centralized planning tiers identify optimal resource allocation strategies. This approach limits uncertainty in production, but requires detailed knowledge about the processes and available resources. Also, it is calculated a-priori and therefore not able to adjusted in real time. In contrast, *value-oriented* approaches offer higher flexibility to adapt to changes, as decisions are decentralized along the value stream and individual situations can be resolved in shorter time, as no centralized institution needs to be consulted. However, value-oriented approaches can lead to higher variances along the value stream and optimal resource allocations may be missed through the absence of a central control unit [2].

The second dimension *scale vs. scope* refers to the tradeoff between cost-effective cheap mass production of similar products vs. costly manufacturing of individualized products. In *economies of scale* production costs per unit are minimized, for example, by lowering fixed costs, bulk buying of resources, increased planning, and through division of labor. *Economies of scope* aim at reducing the costs for manufacturing different products, for offering a diverse product portfolio or individualized products. The focus lies in increased flexibility of a company, for example, by producing different products on the same machine or by shorter lead times (ibid).

To compete in globalized markets, enterprises must solve this polylemma and growing interconnectivity of technical systems between different tiers of a production network and across companies are a possible solution [3]. While Enterprise Resource Planning Systems (ERP) and Manufacturing Execution Systems (MES) are increasingly penetrating manufacturing companies and automated processes increase companies' productivity by optimizing the flow of resources and information, there are and always will be human operators in the loop that maintain control, take responsibility, and must have a profound understanding about aspects not modeled in these systems. However, human factors that contribute to efficient and effective decision making in these complex environments are insufficiently understood [4]–[6].

2. Introduction

The amount of information in its various forms has increased in recent years [7]. In consideration of this fact, business organizations are challegened to find proper ways to deal with the huge amount of information in order to meet the competition in global markets. This issue is particularly important for complex logistic networks like supply chains. Effective supply chain management is characterized with fast and economic decisions while considering different network nodes (e.g. suppliers, resellers, consumers…) and their interactions [8]. Enterprise resource planning (ERP) systems are used to provide these complex information in order to support the decision makers. However, human operators of these information systems are faced with an increasing amount of displayed information. Considering that these operators make the final decisions, they are required to use the appropriate information in context of their goals. As an individual's information processing capacity is limited, receiving too much information may result in information overload [7], which impairs effectivity and efficiency of the decision making process. Therefore, it is important to understand and support the perception and processing of complex information with effective visualization to improve the decision quality. In order to develop general display guidelines, it is indispensable to consider the effects of multiple factors in a controlled experimental setup [9]. Consequently, we first outline the characteristics and issues of the visual design of ERP systems. We thereby clarify the need to investigate the role of information complexity and presentation of the displayed data in ERP system with consideration of human factor. Next, we present an empirical study to deal with the effects of these factors on decision quality. Finally, we discuss the results and provide several important practical implications.

Fig. 1. Screenshot of SAP ERP.

2.1. ERP systems and usability of ERP systems

The implementation of an ERP system is a huge investement for companies (over $1 billion for a large company; [10]). However, the costs are mostly justified: ERP systems are the basis of information processing in companies and thus they have a direct impact on the economic success (productivity, quality, customer satisfaction, fulfillment of industry-specific requirements for documentation and traceability of business processes). The current ERP systems offer integrated software solutions for administration and for planning and control of the operational value creation processes. ERP systems are commercially available for a long time, but they only interact in a very limited way with technical development tools. Despite the benefits of ERP systems, the complexity of these systems is a big point of criticism[11]. The major component of an ERP systems is a tabular presentation of alphanumeric and multi-dimensional data sets. Fig. 1 shows one example of the tabular representation of data in an ERP system.

In order to make proper decisions, users are usually required to scan and integrate various data values [12]. Since users mostly act as final decision makers, the complexity of the displayed information can have a substantial impact on the decision quality. Therefore, information complexity should always be considered in context of ERP systems.

Assuming that the information complexity is constituted by the complexity of the supply chain, it is difficult to manipulate this aspect for a software designer. Thus, the way the information is presented to users is of particular importance. Furthermore, the customer support is becoming increasingly important for many ERP system vendors [13]. In view of these facts, usability may be one of the key factors. DIN EN ISO 9231, Part 11, defines *Usability* is as "the extent to which a product can be used by specified users in a specified way of use to achieve specified goals in an effective, efficient and satisfactory way"[14]. Although the consistent consideration of basic usability criteria proven effect on the performance [15], [16] usability is so far still a subordinate criterion for the design of software systems. It is seen more as a cosmetic facet than a fundamental requirement for optimum performance [17]. In consideration of the highly complex information this is particularly problematic. On the one hand users need more time to complete tasks with more complex ERP interfaces [18]. On the other hand the ease of use is a central determinant of end-user satisfaction with ERP systems [19]. Since successful performance determines the perceived ease of use of a system [20], there is a close relation between subjective ratings and objective performances. So far the evaluation of the usability of ERP and information systems due to the complexity of the required business background and the large number of evaluation criteria is still not implemented consistently. Empirical studies with objective measures (e.g. performance time) can provide among other things further information for the development of evaluation criteria. Therefore, we considered usability and user characteristics in our study. Since information presentation is a key aspect of user interfaces in ERP systems [11], we restricted our study on this factor. In the following section, we describe in more detail the theoretical background to evaluate the factors information complexity and presentation in a user study.

2.2. Evaluation of information complexity, presentation and human factors

In order to get a deeper understanding of the role of information complexity, we subdivided this criticial factor into the factors data amount and task complexity. A similar concept was used in a study concerning accounting and information systems by Iselin. The author divided information load into "the quantitiy of different dimensions and

the quantity of repeated dimensions" [21]. Data amount is also defined as the quantitiy of repeated dimensions in our study. The current stock of a product to different times would be an adequate example in terms of ERP systems. Task complexity basically describes the quantitiy of different dimensions. We extended the definition based on descriptions of Wood [22] and Speier, Vessey und Valcaich [23]. According to these studies, the number of cues necessary for a decision increases with increasing task complexity. Therefore, complex tasks require the acquirement of more dimensions in order to make a proper decision. If the current stock of the product of the previous example consists of two different stores, the task complexity would be higher. Users have to consider two different dimensions (store 1 and store 2) in order to find out the total stock for the product.

The change of font sizes is a common procedure to display more data on a screen. Hence, the manipulation of the size of the displayed data is suitable to investigate the role of information presentation as a key aspect of usability.

Finally, users have to process the displayed data. As already mentioned they take on a role of a final decision maker. User may differ in their ability to process information or select different strategies due to their experiences and cognitive abilities. In the context of information processing, the latter is of particular importance, because humans have limited cognitive processing capacity [24]. Consequently, it is nessecary to examine the role of human factors on the decision quality.

In summary, it seems that information complexity (data amount and task complexity) and presentation are important factors of the visual design of ERP systems. In the present experiment, we examine the interrelationship of these factors in a controlled experiment using a simplified task with simulated ERP system data. In addition, we considered the possible impact of human factors on the decision quality. In the following, we describe the methodology and the results of our experiment.

3. Method

3.1. Experimental task

We constructed alphanumeric tables with simulated ERP system data. Subjects had to use these tables to decide if there was enough total stock to meet the demand of a customer. Tables consisted of four columns and four or eight rows. Each row represented one product and the cells contained numeric data values. The information to each product were divided into the four columns *store*, *production*, *week* and *demand*.

Store (S): The value in this column represented the number of products in the store. The values were randomly generated between 11 and 19.

Production (P) and week (W): The product of these values represented the number of products in the production hall. These products were part of the current stock even though not yet transported to the store. The value for one column was randomly generated between 3 and 9. The value of the other column were varied as a function of the independent variable task complexity.

Demand (D): The value of this column represented the stock demand of a fictive customer. The values differed randomly from 1 to 10 as a function of the total stock in both directions.

The total stock (TS) of a product in each row was calculated by the formula $TS = S + P * W$ and the subjects had to decide for each row if there were enough products (TS > D) or not (TS < D). The final decision referred to the entire table. Therefore, the decision "insufficient total stock" could be made once an insufficient stock was detected for one product, whereas the subjects had to check each row of the entire table for the decision "sufficient total stocks". Fig. 2 shows an example of a table.

Store	Production	Week	Demand
14	3	2	17
13	3	2	12
12	2	9	31
12	9	2	25

Fig. 2. Example of a table with small data amount and high task complexity.

3.2. Experimental variables

We considered decision (sufficient or insufficient stocks) as an independent variable. The dependent variables were performance (reaction times in ms) and accuracy (percentage of correct responses). Furthermore, we examined the effects of the following three major independent variables:

Data amount: We operationalized data amount in two steps by manipulating the amount of rows in the tables. Tables with a small data amount contained four rows and tables with a large data amount contained eight rows. Consequently, subjects had to consider more products for their final decision using tables with a large data amount.

Task complexity: Three levels of task complexity were simulated by using different values for the columns production or week. Tables with low task complexity only required the comparision of the values for store (S) and demand (D), as either the column production or the column week was zero (P or W = 0). Tables with an intermediate task complexity contained the value one (P or W = 1) and tables with a high task complexity the value two (P or W = 2). Therefore, subjects were forced to integrate more dimensions to make a correct decision with increasing task complexity. Each table had the same task complexity across its rows.

Presentation: We used small (Arial, 8 pt, 2.8 mm) and medium (Arial, 16 pt, 5.6 mm) font sizes to construct tables with either poor or good data presentation. As row pitches were modified proportionally, tables with a good presentation were twice as big as tables with a poor presentation. As a consequence poor presentations were indicated with a high local density [25].

3.3. Stimuli and apparatus

Tables were presented on an Apple 24" iMac with a pixel density of 94 ppi (*1920×1200px^2*). The viewing distance was approximately 50 cm. The tables were constructed using the font Arial and a constant size for the labels of the columns and the values of the practice blocks (12 pt, 4.2 mm). We used random numbers for the cells within predefined ranges. In order to avoid unintended effects by the stimuli, we created two different blocks with 96 tables (48 tables for each font size) and equally allocated the participants to the different blocks.

3.4. Participants and user characteristics

A total of 32 participants (13 female) volunteered to take part in the study and received a small present in return. The age ranged between 21 and 39 years (M = 26.47; SD = 4.73) and most participants were students. All participants reported normal or corrected-to normal visual acuity. We randomly assigned the particpants to the good and poor data presentation group by their sex ($N_{female; poor} = 6$; $N_{female; good} = 7$).

We controlled for different individual characteristics that were thought to influence performance. In addition to the expertise of the participants, we measured the cognitive abilities perceptual speed and numeracy. In the following we only report the scores of 31 participants, because we had excluded one male participant from the later analysis (see below, $N_{poor} = 15$; $N_{good} = 16$).

Expertise: We measured the expertise in interacting with numerical data using four 7-point Likert items (Min = 1; Max = 7). We considered the frequency for working with tables and numbers (e.g. "I often work with numbers.") and the subjective interest (e.g. "I like working with tables."). Overall, participants were quite experienced (M = 5.10; SD = 1.22 and there were no significant differences between the good and poor data presentation group.

Cognitive abilities: Numeracy was measured using an addition test from the kit of factor-referenced cognitive tests [26]. In this test the participants had to sum up three digit numbers with a time limit. The average score of the 120 possible points was 28.26 (SD = 8.16) with no significant differences between both groups. We used the number-comparison test [26] in order to assess the perceptual speed. Here, the participants had to detect differences between multi-digit numbers with a time limit. Participants scored in average 25.23 (SD = 5.01) from 51 possible points. The scores differed significantly between the two groups. The poor presentation group reached a higher score ($M_{poor} = 28.10$; $SD_{poor} = 4.92$) than the good presentation group ($M_{good} = 22.69$; $SD_{good} = 3.57$; t(29) = 3.50; p < .001). We considered this difference in our further analysis.

3.5. Design and procedure

The experiment was based on a 2 x 2 x 3 x 2 experimental design with three within-subjects factors and one between factors. The within-subject factors were decision (insufficient, sufficient), data amount (small, large) and task complexity (low, intermediate, high) and the between-subject factor presentation (good, poor).

Participants attended the experiment individually. The experiment began with the completion of the expertise questionnaire and the conduction of the cognitive tests. The experimenter explained then the experimental task and instructed the participants to respond as fast and accurately as possible. The participants were allocated to the experimental block (48 tables) after a practice block with 12 tables. The order of trials was individually randomized. At the beginning of each trial, a fixation cross was presented at the center of the screen. The table appeared on the screen 250 ms after the fixation cross appearance. The participants responded with either their left ("sufficient stocks") or right ("insufficient stock") index finger to make a decision. Reaction time was measured from the appearance of the table until the participant's response. The experiment lasted about 40 min.

4. Results

The mean reaction time for all correct trials (92.90 %) was 10.19 s (SD = 6.61 s). One participant was excluded from the further analysis due to long (RT>>M+SD) reaction times. As a result of the high standard deviations we used the median values for for the further analysis. The significance level was set at $p < .05$. Furthermore, we used the sphericity assumption and the Greenhouse-Geiser method for the data interpretation. First, it was checked if there were correlations between the user characteristics (expertise, numeracy and perceptual speed) and the performance (reaction times of correct trials and errors). It showed that there were a marginal significant negative correlation between the perceptual speed score and the reaction times ($r = - .51$; $p = .05$). Since there were also differences between both presentation groups concerning this score, we considered perceptual speed as a covariate. As a consequence, ANOCOVAs on median reaction times of correct trials and mean correct percentages were conducted with the within-subject factors decision (sufficient, insufficient), data amount (small, large), task complexity (low, intermediate, high) and the between-subject factor presentation (good, poor). The ANCOVA on the correct percentages showed no signifinance effects. In the following, we report the results of the ANCOVA on the reaction times. A significant main effect of decision was found ($F(1, 28) = 4.87$, $p < .05$, $\eta^2 = .15$). Reaction times for tables with an insufficient stock ($Mdn_{insufficient} = 8.71$ s) were faster than for tables with sufficient stocks for all products ($Mdn_{sufficient} = 11.71$ s). There were also a significant main effect of data amount ($F(1, 28) = 18.94$, $p < .001$, $\eta^2 = .40$). Participants responded faster to tables with a small data amount ($Mdn_{small} = 6.48$ s) than to tables with a large data amount ($Mdn_{large} = 11.24$ s). Also, a main effect of task complexity was present ($F(1.59, 44.43) = 11.76$, $p < .001$, $\eta^2 = .30$). Paired t-tests with Bonferroni corrections showed significant effects between all steps ($< p .001$), indicating that reaction times increase with complexity ($Mdn_{low} = 6.03$s; $Mdn_{intermediate} = 8.66$s; $Mdn_{high} = 12.55$s).

The interaction between data amount and task complexity was also observed ($F(1.48, 41.31) = 5.44$, $p < .001$, $\eta^2 = .32$). As can be seen from Fig. 3 (a), the negative impact of a large data amount was much more pronounced for tables with higher task complexity ($F(1, 28) = 9.48$, $p < .01$, $\eta^2 = .25$).
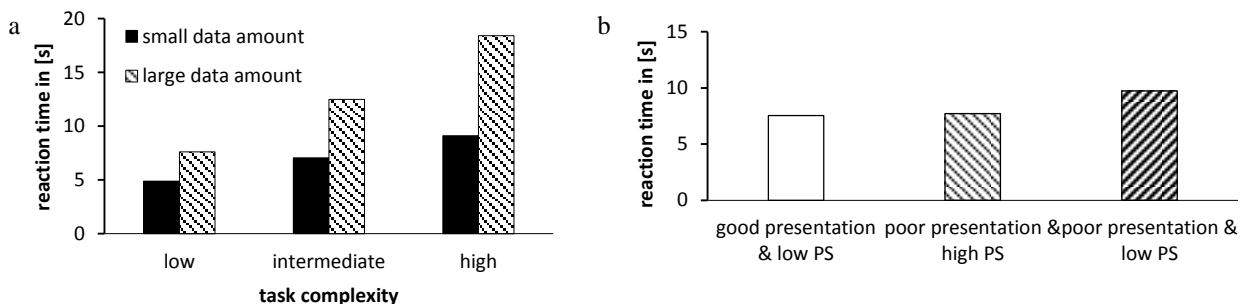

Fig. 3. Interaction between task complexity and data amount for the reaction times in [s] (a). Main effect of classification (presentation and perceptual speed; PS) for the reaction times in [s] (b).

The analysis revealed a main effect of presentation. Participants of the good presentation group responded faster (Mdn_{good} = 7.53 s) than participants of the poor presentation group (Mdn_{poor} = 8.84 s). Since there was also a significant effect of the covariate perceptual speed ($F(1, 28)$ = 4.64; $p < .05$; η^2 = .14), we examined the perceptual speed scores (PS_{Score}) of both presentation groups in more detail. It becomes apparent, that the maximum score for the good presentation group (Max_{good} = 28 s) was only just above the median test score for the poor presentation group (Mdn_{poor} = 28 s). For this reason, we divided the participants into three groups: nine participants with poor presentation and low perceptual speed ($PS_{Score} \leq 28$), six participants with low presentation and high perceptual speed ($PS_{Score} > 28$) and sixteen participants with good presentation and low perceptual speed ($PS_{Score} \leq 28$). We conducted a repeated-measures ANOVA on the reaction times with the usual within-subject factors (decision, data amount and task complexity) and the new between subject factor classification (poor presentation and low PS_{Score}, poor presentation and high PS_{Score}, good presentation and low PS_{Score}). We found the same significant results as before and in addition a significant main effect of classification ($F(1, 28)$ = 8.12, $p < .01$, η^2 = .37). This effect is illustrated in Fig. 3 (b). Subsequent paired *t*-tests with Bonferroni corrections revealed that participants with a poor presentation and low perceptual speed responded significantly slower ($Mdn_{poor;low}$ = 9.74 s) than participants with a poor presentation and high perceptual speed ($Mdn_{poor;high}$ = 7.72 s; $p < .01$) and than participants with a good presentation and low perceptual speed ($Mdn_{good;low}$ = 7.53 s; $p < .01$). As can be seen from Fig. 3 (b), there was no significant difference between the latter classification groups.

5. Discussion

The indisputable benefits of increased interconnectivity of production machinery, manufacturing execution systems, and enterprise resource planning systems for small to cross-national companies are challenged by the growing complexity of the user interfaces of these systems. In order to fully harness the power of the growing number and granularity of available information the technical and human factors that contribute to an understanding of the presented information and to high decision efficiency and effeciticty must be thouroughly understood.

The current study examined the effects of information complexity (data amount and task complexity) and visual presentation as a key aspect of usability and human factors on the decision efficiency and effectivity in MES and ERP systems. The purpose of this study was to investige the interrelationship of these factors and to derive practical implication for the design of future MES and ERP systems. The findings showed that decision speed dropped with increasing data volume and task complexity. In addition, the negative impact of increasing data volume on decision speed was particularly large for tables with high task complexity. Furthermore, it was found that poor presentation decreased the decision speed. Individual differences in form of perceptual speed also influenced decision speed and the study revealed that poor presentations especially impaires people with lower perceptual speed. Contrary, people with high perceptual speed can compensate poor presentations and achieved about the same level of decision speed as individuals with low perceptual speed using good presentations.

The implication of this study are manyfold. First, the study revealed that decision performance is influenced by human factors. Although these precise nature of this influence is not yet sufficiently understood the presented experimental paradigm offers the potential to thoughly investigate the role of technical and human factors in complex environments and to quantify the costs of poor interfaces as a function of human factors. The sample consisted of a homogeneous group of experienced and rather fast participants. Hence, further multi-factorial experiments with a more diverse sample that resembles the typical workforce (age, perceptual speed, motivation, …) are neccessary to better understand the interrelationship of the investigated factors and to reveal possible interaction effects between these factors (e.g., perceptual speed, data amount, and task complexity).

Second, the study showed that people with a high perceptual speed are able to compensate negative effects of poor usability. We speculate that developers of MES or ERP systems have overlook that their systems are used by a diverse user population with a large variance in age, motivation, and cognitive abilities, of which not everybody is able to compensate the effects of bad user interfaces. We therefore suggest that MES and ERP systems are systematically reengeinnered following the typical usability lifecycle as suggested by Gould and Lewis (early focus on users, empirical measurement of usage, and iterative design) [27] and that available guidelines for reducing complexity are systematically applied [4], [6], which includes a consideration of different aspects of information

complexity and their possible interactions. It is crucial that software developers pay attention to factors of user diversity, such as age and cognitive abilities, as these substantially contribute to inceased effectivity, efficiency, and satisfaction and which will eventually yield in substantially more productive and competitive companies.

Acknowledgement

References

[1] C. Brecher, Ed., Integrative Production Technology for High-Wage Countries. Springer Heidelberg Dorbrecht London New York, 2012.
[2] R. Schmitt, et al., "Self-optimising Production Systems," in Integrative Production Technology for High-Wage Countries, C. Brecher, Ed. Springer Heidelberg Dorbrecht London New York, 2012, pp. 697–986.
[3] G. Schuh, V. Stich, T. Brosze, S. Fuchs, C. Pulz, J. Quick, M. Schürmeyer, and F. Bauhoff, "High resolution supply chain management: optimized processes based on self-optimizing control loops and real time data.," Production Engineering, vol. 5, no. 4, pp. 433–442, 2011.
[4] A. Calero Valdez, P. Brauner, A. K. Schaar, A. Holzinger, and M. Ziefle, "Reducing Complexity with simplicity - Usability Methods for Industry 4.0," in 19thTriennial Congress of the International Ergonomics Association (IEA 2015), 2015, p. (in press).
[5] P. Brauner, S. Runge, M. Groten, G. Schuh, and M. Ziefle, "Human Factors in Supply Chain Management – Decision making in complex logistic scenarios," in Proceedings of the 15th HCI International 2013, Part III, LNCS 8018, 2013, pp. 423–432.
[6] P. Brauner and M. Ziefle, "Human Factors in Production Systems – Motives, Methods and Beyond," in Advances in Production Technology, C. Brecher, Ed. Springer International Publishing, 2015, pp. 187–199.
[7] A. Edmunds and A. Morris, "Problem of information overload in business organizations: A review of the literature," International Journal of Information Management, vol. 20, no. 1, pp. 17–28, 2000.
[8] D. Simchi-Levi, P. Kaminsky, and E. Simchi-Levi, Designing and Managing the Supply Chain: Concepts, Strategies, Case Studies,. 2003.
[9] J. Meyer, D. Shinar, and D. Leiser, "Multiple Factors that Determine Performance with Tables and Graphs," Human Factors: The Journal of the Human Factors and Ergonomics Society, vol. 39, no. 2, pp. 268–286, 1997.
[10] I. J. Chen, "Planning for ERP systems: analysis and future trend," Business Process Management Journal, vol. 7, no. 5, pp. 374–386, 2001.
[11] A. Singh and J. Wesson, "Evaluation criteria for assessing the usability of ERP systems," in Proceedings of the 2009 Annual Research Conference of the South African Institute of Computer Scientists and Information Technologists, 2009, pp. 87–95.
[12] A. Parush, A. Hod, and A. Shtub, "Impact of visualization type and contextual factors on performance with enterprise resource planning systems," Computers & Industrial Engineering, vol. 52, no. 1, pp. 133–142, 2007.
[13] M. Bayer and J. Hill, "ERP-Zufriedenheit: Bessere Flexibilität," Computerwoche, no. 38, 2012.
[14] DIN/EN/ISO 9241:11 Ergonomic requirements for office work with visual display terminals: Guidance on usability. 1998.
[15] S. Oetjen and M. Ziefle, "A visual ergonomic evaluation of different screen types and screen technologies with respect to discrimination performance," Applied Ergonomics, vol. 40, pp. 69–81, 2009.
[16] R. Philipsen, P. Brauner, S. Stiller, M. Ziefle, and R. Schmitt, "Understanding and Supporting Decision Makers in Quality Management of Production Networks," in Advances in the Ergonomics in Manufacturing. Managing the Enterprise of the Future 2014 : Proceedings of the 5th International Conference on Applied Human Factors and Ergonomics, AHFE 2014, 2014, pp. 94–105.
[17] M. Ziefle and E.-M. Jakobs, "New challenges in human computer interaction: Strategic directions and interdisciplinary trends," in 4th International Conference on Competitive Manufacturing Technologies, 2010, pp. 389–398.
[18] N. E. Park, "Testing & Quantifying ERP usability," in Proceedings of the 1st Annual conference on Research in Information Technology (RIIT), 2012, pp. 31–36.
[19] C. Ozen and N. Basoglu, "Impact of Man-Machine Interaction Factors on Enterprise Resource Planning (ERP) Software Design," in Portland International Conference on Management of Engineering and Technology, 2006, vol. 5, pp. 2335–2341.
[20] K. Arning and M. Ziefle, "Understanding age differences in PDA acceptance and performance.," Computers in Human Behavior, vol. 23, no. 6, pp. 2904–2927, 2007.
[21] E. R. Iselin, "The effects of information load and information diversity on decision quality in a structured decision task," Accounting, Organizations and Society, vol. 13, no. 2. pp. 147–164, 1988.
[22] R. E. Wood, "Task complexity: Definition of the construct," Organizational Behavior and Human Decision Processes, vol. 37, no. 1. pp. 60–82, 1986.
[23] C. Speier, I. Vessey, and J. S. Valacich, "The Effects of Interruptions, Task Complexity, and Information Presentation on Computer-Supported Decision-Making Performance," Decision Sciences, vol. 34, no. 4, pp. 771–797, 2003.
[24] G. A. Miller, "The magical number seven, plus or minus two: Some limits on our capacity for processing information," Psychological Review, pp. 81–97, 1956.
[25] T. S. Tullis, "The Formatting of Alphanumeric Displays. A Review and Analysis," Human Factors, vol. 25, no. 6, pp. 657–682, 1983.
[26] R. B. Ekstrom, J. W. French, H. H. Harman, and D. Dermen, "Kit of factor-referenced cognitive tests," Princeton NJ., 1976.
[27] J. D. Gould and C. Lewis, "Designing for Usability: Key Principles and what Designers Think," Communications of the ACM, vol. 28, pp. 300–311, 1985.