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Individual Ability-Based System Design of Dependable Human-Technology Interaction

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Abstract: This paper highlights the importance of considering especially individual differences in intelligence when designing systems and interfaces due to their impact on operator performance in new and unfamiliar situations. For this purpose, an approach is introduced which allows assessing performance-relevant abilities of the operators on the basis of their performance on everyday life tasks. In order to increase the overall human-machine system dependability, guidelines are derived about appropriate reconfigurations of the technical system and/or its interface on the basis of the assessed performance-relevant abilities. The impact of this new approach to dependable system and interface design is discussed.

1. MOTIVATION: HUMAN-CENTERED TECHNOLOGY

Research in the field of human-centered technology is often motivated by developing technical systems which optimize the overall system performance in normal situations, in unanticipated circumstances and during system breakdowns. Two approaches to achieve this goal can be distinguished and are described in the following.

1.1 Definition of an optimal " level of automation"

Some human-centered technology researchers aim at defining an optimal "level of automation", i.e., the level of autonomy with which the technical system pursues its functions and at which the human-machine system performs best (e.g., Endsley & Kaber, 1997; Parasuraman, Sheridan, & Wickens, 2000). Other researchers focus on specifying when the operator should be supported with automated functions to balance his/her current workload and, therewith, achieve a high overall performance level (e.g., Byrne & Parasuraman, 1996; Hancock, Chignell, & Lowenthal, 1985), which is defined on the basis of the task's degree of fulfillment. Both fields, i.e., the static definition of an ideal level of automation and the adaptive allocation of functions to the human operator or the machine, have also been combined (see e.g., Kaber & Endsley, 2004).

1.2 Interface design

Other approaches to enhance the performance of human-machine systems aim at ameliorating the communication between the user and a machine. For this purpose, various guidelines for optimal interface design have been published. Examples are the Direct Manipulation Interface (DMI, Shneiderman, 1983), the Ecological Interface Design (EID, Vicente & Rasmussen, 1992), the Intuitive Interfaces (Baerentsen, 2000) or the Delegation-Type Interfaces (e.g., Parasuraman, Galster, Squire, Furukawa & Miller, 2005).

The DMI has been defined by Shneiderman (1983) as an interface allowing the user to directly manipulate objects presented on the display. This manipulation should correspond at least loosely with the according manipulations in the physical/real world. The overall goal of the DMI is to make the interaction easier to learn, to give the operator incremental and rapid feedback, to complete tasks in less time and to make the overall system more dependable by reducing the number of human errors performed.

The EID (Vicente & Rasmussen, 1992) extends the DMI and aims at providing optimal support for each level of cognitive control. The concept of cognitive control is based on the Skills, Rules, and Knowledge (SRK) model introduced by Rasmussen (1983), who distinguished three ways of interaction between human beings and their environment depending on the degree of novelty of a situation:

1) Skill-based behavior (SBB) is highly automated, unconscious behavior, representing fluid sensory-motor performance. The perceptual-motor system controls the human behavior.
2) Rule-based behavior (RBB) is controlled by rules or procedures, which are rules of thumb or effective know-how. These rules are empirically derived informal cues that discriminate between the perceived action possibilities and allow choosing the supposedly best one without investigating great cognitive effort.
3) Knowledge-based behavior (KBB) takes place in unfamiliar, unanticipated situations, in which no rules are available (Vicente & Rasmussen, 1992). In such new situations, the human being formulates goals based on analyzing the environment and the overall aims. Based on these goal formulations, plans are developed and selected to achieve the goals. The effects of different plans are tested based on internal representations or by experiments.

To support these three levels of cognitive control, the following guidelines are provided by the EID (Vicente & Rasmussen, 1992):

1) SBB can be supported best if the interface provides the means to act directly on the display. The information on the display should be isomorphic to the structure of corresponding movements.
2) In order to support RBB, the interface should provide cues or signs which optimally map the constraints of the work domain in question.
3) To support KBB, the interface should display the relational properties of the work domain in the form of an abstraction hierarchy, which serves as an externalized mental model (see e.g., Vicente & Rasmussen, 1990). This mental model provides appropriate support for planning activities and thought experiments.

The applicability of these guidelines have e.g. been empirically tested by Vicente, Christoffersen, and Pereklita (1995), and yielded experimental support.

1.3 Relevance of individual differences

The known interface design guidelines and approaches to statically or dynamically adapt the automated functions to optimize the performance of the human-machine system only consider the user in a very general way but ignore differences between users (but see research on dynamically allocating automated functions to the machine or the operator depending on his/her current level of workload as conducted e.g., by Parasuraman, 1990).

The importance of considering individual differences is especially at hand when discussing the EID: The three levels of cognitive control proposed by the SRK model closely resemble the three phases of skill acquisition (see e.g., Fleishman, 1972):

The first phase of skill acquisition takes place when the user is confronted with a situation the first time: Attention is focused on thoroughly understanding the task in question, building a cognitive representation, and working out a (potentially successful) solution. Performance is slow and error-prone. The description of this phase resembles the KBB. When an adequate cognitive representation of the task has been built, the learner proceeds to the second phase of skill acquisition and easier ways of achieving the same result are defined. Rules are worked out and fine-tuned. RBB takes place. In the last phase of the skill acquisition process, performance is fast and accurate. The task is fully automated and can be completed without much attention. SBB is controlling human behavior.

Ackerman (1988) explained the performance of human beings in these three levels of cognitive control (according to Rasmussen, 1983) or phases of skill acquisition (according to Fleishman, 1972) on the basis of individual differences in relevant abilities (see Fig. 1). The author proposed that performance in the first phase of skill acquisition (or KBB) is determined by general intelligence, performance in the second phase, i.e., the RBB by perceptual speed and the performance in the third phase, i.e., the SBB by motor abilities.

General intelligence was defined by Ackerman (1988) in accordance to Humphreys (1979), as the ability to acquire, store, retrieve, combine, compare, and use information in new, other contexts. The core cognitive activity of perceptual speed is to generate rules to effectively solve easy tasks; hence, perceptual speed is the speed with which such simple rules can be implemented and compiled. Last, psychomotor abilities are independent from information processing and represent individual differences in the speed/accuracy of motor responses to tasks without information processing demands.

Hence, highly intelligent operators will be advantaged, and make less serious errors when having to deal with an unknown and unanticipated situation compared to a less intelligent operator (see also Fig. 1): The ability/performance correlation is greater for the more intelligent users. This is especially important, as, according to Vicente and Rasmussen (1992) the problem solving behavior is particularly safety-critical when confronted with new situations. Ackerman's skill acquisition theory (1988) implies that the new situation is less safety-critical for highly intelligent users but reducing the complexity of the situation and, thus, the need for general intelligence to be involved in working out the best solution, will also make the situation less safety-critical (Ackerman, 1988). This advantage of the highly intelligent users will disappear with the degree of familiarity of the situation, as other abilities will then determine performance.

The relationship between the impact of errors and the higher cognitive processes involved has e.g., been shown empirically by Hammond, Hamm, Grassia, and Pearson (1987).

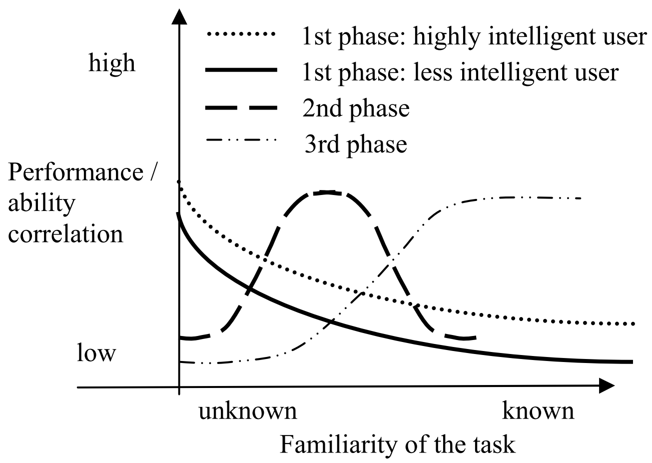

Fig. 1. Phases of skill acquisition adapted from Ackerman (1988) and the impact of general intelligence on the performance/ability correlation.

As intelligence is not considered a single ability construct (see also Section 4.1), but a complex structure of cognitive abilities, not only general intelligence but also the operator's structure of intelligence is to be considered. The content abilities (i.e., verbal, numerical and figural intelligence) will impact the quality of interaction between the operator and the system's interface, while the operation abilities (i.e., reasoning, perceptual speed, memory, creativity) will determine the quality of interaction between the technical system and its operator when being confronted with a new situation.

2. PROBLEM STATEMENT

For a human-machine system it is required to find a method to assess the dependability-relevant characteristics of the operator (such as e.g., intelligence) and adapt the human-machine system/interface such that the overall system-performance is increased.

3. SOLUTION APPROACH

In order to be able to reconfigure the technical system and/or its interface based on its user's abilities, two steps are necessary: First, an algorithm must be developed which is capable of assessing the dependability-relevant characteristic of the user in an automated manner on the basis of the operator's performance on his/her everyday life tasks (see Section 3.1). Second, guidelines must be defined specifying how the system/interface should be reconfigured depending on the level of the relevant ability of the current user and the demands of the system (see Section 3.2). This general procedure is derived from psychological diagnostics (see e.g., Amelang & Schmidt-Atzert, 2006), which aims at systematically collecting and processing data in order to make decisions about appropriate actions.

3.1 Automated assessment of relevant user characteristics

Traditional tests to measure the individual levels of abilities such as intelligence (e.g., Jäger, Süß, & Beauducel, 1997) could be applied in this context as well. Although these tests exist in computer-based versions, they have the following disadvantages:

- Automated assessment is not possible.
- Applying the existing tests requires lots of time.
- An investigator is required to explain and guide the test procedure.
- Tests are not highly accepted by users.
- Tests consist of artificial tasks.

Hence, a new and especially automated testing procedure needs to be developed, which, first, should give a valid measurement of the characteristic of interest and, second, should make use of data from tasks the user already executes in everyday life.

This proposed testing procedure is based on the item response theory IRT (Hambleton, Swaminathan, & Rogers, 1991). IRT assumes that a behavior (i.e., the response RA_{ji} on the task A_j, j=1..m from person i=1..n) is an indicator of a latent dimension/characteristic such as intelligence I=1..g (i.e., ξ_{Ii} with $-\infty < \xi_{Ii} < +\infty$). As mentioned before, different types of intelligences I can be distinguished (see also Section 4.1).

The distinction between behavior and latent dimensions is necessary, as the latter cannot be measured directly and can only be assumed based on the "observable" or manifest variables RA_{ji} and their correlations. RA_{ji} is coded as follows:

$$RA_{ji} \begin{cases} 1 & \textit{if the answer is correct} \\ 0 & \textit{if the answer is wrong} \end{cases}$$

The relationship between the manifest variables and latent dimensions is given by the item characteristic curve ICC. The ICC is a function (1) of the latent characteristic ξ_{Ii}, the difficulty σ_{Ij} of the current task j, to which solution the latent dimension of the relevant ability ξ_{Ii} contributes (with $-\infty < \sigma_{Ij} < +\infty$). It describes the probability of whether the task will be achieved by the person or not. While σ_{Ij} is referred to the task parameter, ξ_{Ii} is also named the person parameter.

$$P(RA_{ji} = 1) = F(\xi_{Ii}, \sigma_{Ij}) \tag{1}$$

Depending on the characteristics of the task j, the properties of the responses RA_{ji} and the latent dimension ξ_{Ii} in question, different ICCs and underlying mathematical functions can be distinguished.

An example is the "Rasch Model" (see e.g., Hambleton, Swaminathan, & Rogers, 1991), which is a logistic function (2) predicting the probability of a correct answer $RA_{ji} = 1$ to a task j with the task difficulty σ_{Ij} from a person i with the ability ξ_{Ii}.

$$P(RA_{ji} = 1 \mid \xi_{Ii}, \sigma_{Ij}) = \frac{e^{\xi_{Ii} - \sigma_{Ij}}}{1 + e^{\xi_{Ii} - \sigma_{Ij}}} \tag{2}$$

The function implies that for a person i, for whom $\xi_{Ii} < \sigma_{Ij}$, the probability that he/she will solve the task j successfully is p < .50 (see Fig. 2). If, the task difficulty σ_{Ij} equals the person parameter ξ_{Ii} the probability that the task will be solved successfully by person i equals p = .50. Last, if $\xi_{Ii} > \sigma_{Ij}$, the probability that the task j will be solved by person i is p > .50.

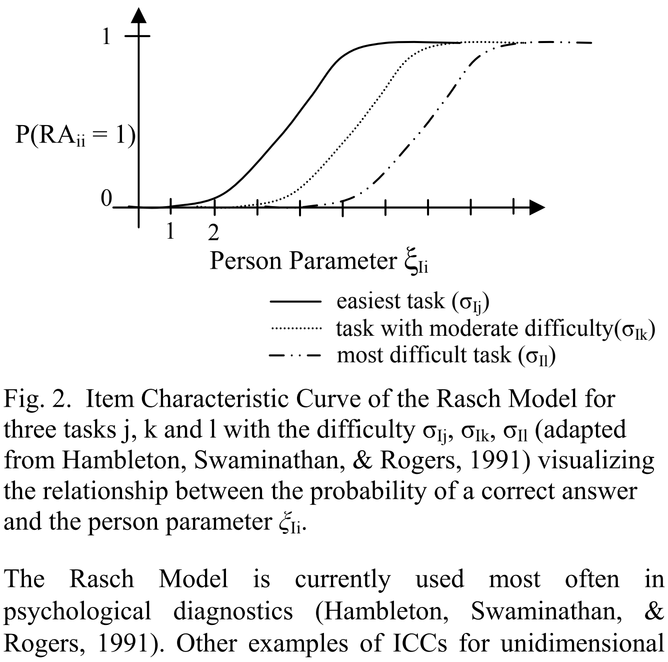

Fig. 2. Item Characteristic Curve of the Rasch Model for three tasks j, k and l with the difficulty σ_{Ij}, σ_{Ik}, σ_{Il} (adapted from Hambleton, Swaminathan, & Rogers, 1991) visualizing the relationship between the probability of a correct answer and the person parameter ξ_{Ii}.

The Rasch Model is currently used most often in psychological diagnostics (Hambleton, Swaminathan, & Rogers, 1991). Other examples of ICCs for unidimensional tasks are e.g., the Birnbaum model or the three-parameter logistic model. The assumption of the unidimensionality, which underlies all these three models, requires that the solution of the task j only depends on one latent dimension or ability I. As, in this application, everyday tasks and no artificially constructed tasks will be applied to assess relevant abilities, it is expected that this assumption does not hold. Instead, it is assumed that the solution of an everyday task depends on the solution of a set of items, each of which is based on one single intelligence or any other latent user characteristic. This means that for each item, the Rasch model is still valid and can be applied. The overall task solution depends on a combination of the solutions of the items.

In order to judge on the dependability-relevant user characteristics, the assessment of this ability needs to be automated. As, with new tasks with unknown characteristics, neither the person parameters ξ_{li}, the task parameters σ_{lj} nor the impact of an item of a task on the task's solution q_{ij} are known, a two-step identification procedure e.g., on the basis of an Artificial Neural Network is required to estimate ξ_{li}.

In the first step, a preferably heterogeneous number of persons will be tested with a traditional ability test to assess the ability vector $\boldsymbol{\xi_i} = (\xi_{1i}..\xi_{gi})$ for the sample at hand. The results of these traditional tests will be fed into a function $A_j = F(\boldsymbol{\xi_i}, \sigma_{ij}, q_{ij})$, which represents a task A_j and which will estimate RA_{ji}, i.e., whether a person i will succeed when performing a given set of tasks. This function will be based on the Rasch model. The impact of an task's item on the solution of the overall task is q_{ij}. The parameters of the function (i.e., q_{ij} and σ_{ij}) will be trained using the error between the estimated RA_{ji} and the actually measured RA_{ji}. In order to derive these reference values RA_{ji}, the sample at hand will repeatedly execute a (preferably heterogeneous) set of tasks.

In the second step, the answers RA_{ji} of a (new) sample on a given set of tasks is known and what is required is their ability structure $\boldsymbol{\xi_i}$. The corresponding function $F(RA_{ji})$, which determines $\boldsymbol{\xi_i}$, will be approximated by an Artificial Neural Network.

This described two-step procedure is depicted in Fig. 3.

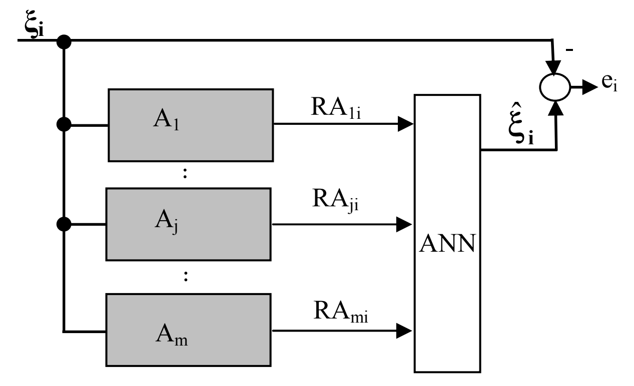

Fig. 3. Block diagram of the proposed automated user assessment on the basis of the latent ability structure ξ_i and the tasks A_j.

If the original ability vector $\boldsymbol{\xi_i}$ is heterogeneous and influences the tasks solutions RA_{ji}, the trained Artificial Neural Network can be used to estimate $\boldsymbol{\xi_i}$. These estimated person parameters ξ_{li} can be taken as a reliable and valid predictor of how well the operator will be able to deal with the interface and/or system in question.

3.2 Reconfiguration of the task allocation and/or interface properties

In order to be able to predict how well the operator will be able to manage the technical system and the interface especially in unfamiliar situations, will enable to reduce the error probability and the response time of the operator in an unfamiliar situation by reconfiguring the parameters of the system and/or of the interface.

This can be realized, for example, based on a quality measure of the ability structure of the current operator. The more heterogeneous tasks the operator has conducted and the more RA_{ji} will be available, the greater the reliability of the person parameters will be. The relationship between the number of tasks available and the quality of the person parameter estimation is nonlinear and has e.g., been described by the Spearman-Brown Formula. Based on such a quality or reliability measure, a confidence interval can be put around the assumed person parameter ξ_{li}. Within this interval, the true value is located with a given probability. The worse the quality of the estimation of the ability score, the larger the confidence interval will be.

To derive rules for the system and/or interface reconfiguration, two procedures can be assumed:

First, a critical person parameter can be determined, which the operator must have in order to be able to safely run the technical system in question. This parameter can be used in order to do personnel selection.

Second, the confidence intervals of different ability dimensions of one operator and the difficulty parameters of various tasks can be compared and the task chosen, which matches the ability structure of the operator in question. This procedure is only valid, if the confidence intervals for the abilities of the ability structure indicate that the values are significantly different from each other. If, for example, the confidence intervals of two abilities overlap, it cannot be assumed that the operator's true values on these two abilities differ. However, if the abilities are different from each other, the task, which will evoke less human errors, is the one which requests the user to apply his/her more gifted abilities, when solving the task. The latter assumption is based on research results about Ackerman's skill acquisition theory (see e.g., Jipp, Pott, Wagner, Badreddin, & Wittmann, 2004).

4. EXAMPLE

The example is given to demonstrate and highlight the effect of the proposed dependable system and interface design. For this purpose, first, a multidimensional intelligence model is introduced (see Section 4.1), as well as the practical steps required to perform the proposed automated user assessment of the intelligence abilities (see Section 4.2) and the deduced system and/or interface reconfigurations (see Section 4.3.).

4.1 Berlin intelligence structure model

The Berlin Intelligence Structure Model (BIS) is a hierarchical model of intelligence (Jäger, 1982) and depicted in Fig. 4.

At the top level, general intelligence is composed of two facets, which are categories for factors/latent dimensions on the next level: contents and operations. The first subsumes content abilities, which refer to how a person deals with different types of contents. The facet contents consists of a verbal ability factor (V), a numerical ability factor (N), and a figural-spacial ability factor (F). The facet operations subsumes what is cognitively done with the given material of a special content type. Human processing capacity (P), memory (M), creativity (C) and perceptual speed (S) have empirically been determined by Jäger (1982). Human processing capacity is explained as the ability to solve relative complex problems (Jäger, Süß, & Beauducel, 1997). Memory tasks demand the operator to memorize pieces of information and retrieve them from the short-term memory or recognize them after a short period of time. Creativity refers to the ability to produce different ideas controlled by the task in question. The last operation, perceptual speed, expects the operator to work as fast as possible on simple, cognitive tasks. Hence, general intelligence is defined based on a linear combination of M, C, R, S, V, N, and F. All these "intelligences" are latent dimensions as introduced in Section 2.1.

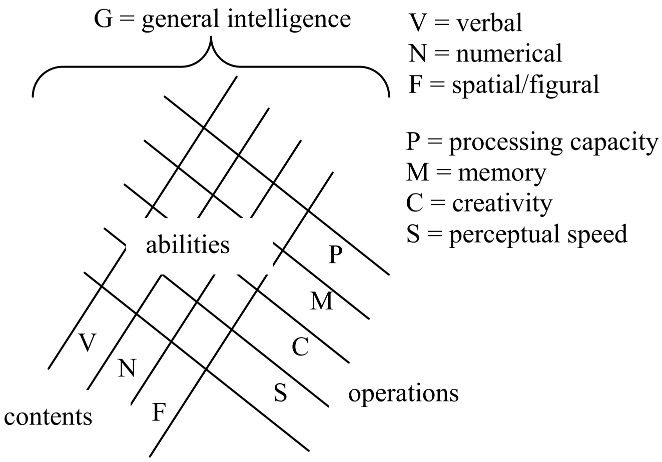

Fig. 4. Berlin Intelligence Structure Model (adapted from Jäger, 1982).

4.2 Automated user assessment of intelligence

Each real-life task j has a mixed set of cognitive requirements, especially when the situation is unfamiliar. For example, choosing the correct action alternative when confronted with a so-far unknown situation in a nuclear power station requires the operator to apply processing capacity (P) in order to reason about the possible causes of the situation and his/her numerical abilities (N) due to the format of the displayed data. Hence, its successful handling depends on the individual levels of the relevant ability vector $\boldsymbol{\xi_i} = (\xi_{Pi}, \xi_{Ni})$, and on their impact on the task's solution (q_{ij}) and the task difficulty parameter (σ_{Ij}). Another task might require the operator to apply other intelligences, such as memory M, processing speed S and verbal abilities V. If the intelligence structure ξ_{Ii} (i.e., the individual level of P, M, C, S, V, N, and F) is known, as well as the impact of each intelligence level on solving the task successfully (q_{Ij}) and the task difficulty (σ_{Ij}), the probability of a correct or incorrect reaction ($P(RA_{ji})$) is given based on the relevant ICC.

To measure the intelligence structure ξ_{Ii} the operator will work on his/her everyday tasks. The reactions will be fed in, for example, an artificial neural network (see Fig. 3), which will, based on the already adapted weights of each intelligence level on the task solution (σ_{Ij} and q_{ij}) and the theoretically proposed ICC, estimate the person parameters ξ_{Pi}, ξ_{Mi}, ξ_{Ci}, ξ_{Si}, ξ_{Vi}, ξ_{Ni},and ξ_{Fi}.

4.3 Reconfigurations of the system and its interface

If the intelligence scores ξ_{Pi}, ξ_{Mi}, ξ_{Ci}, ξ_{Si}, ξ_{Vi}, ξ_{Ni}, and ξ_{Fi} of person i are known, the system design can be adjusted to reduce the error probability in the following manner:

It is expected that the operational abilities and especially the human processing capacity ξ_{Pi} influence the performance of the operator when cooperating with the technical system. The error probability will be increased if operating the system requires a higher level of human processing capacity as the one of the current operator. This is, e.g., the case, when an operator's assessed ability level of P is $\xi_{Pi} = 100$ and operating the system's current configuration requires $\xi_{Pi} = 110$. Then, the system should be reconfigured and the necessity to apply human processing capacity should be reduced. This can, for example, be achieved by enhancing the level of autonomy of the automation system. Endsley and Kaber (1997) define various "levels of automation" depending on what function (i.e. monitoring, generating an action alternative, selection and implementation) is automated. To reduce the required level of human processing capacity, the technology should take over functions such as retrieving information from memory, combining and comparing new and old pieces of information and using the result (Jäger, 1982). Hence, the technical system should provide high levels of automation in respect to generating and selecting appropriate action alternatives (in terms of Endsley and Kaber, 1997), this is the case at the higher levels of automation. Then, the probability that the operator makes an error is reduced. This is an example of the first type of system reconfiguration according to Section 3.2.

In contrast especially to the impact of ξ_{Pi} on the optimal "level of automation", the content abilities ξ_{Vi}, ξ_{Ni}, and ξ_{Fi} are expected to influence the cooperation with the system's interface. For example, an interface with lots of numerical contents will require a high level of numerical abilities by the operator in order to process the information. However, if the operator's numerical abilities are less compared to, e.g., the figural abilities (e.g., $\xi_{Ni} = 90 < \xi_{Fi} = 100$), the interaction with the operator would be less error-prone if the system displayed the same information in a figural format. This is an example of the second type of interface reconfiguration as described in Section 3.2.

5. DISCUSSION AND CONCLUSIONS

This paper presents a novel approach to dependable humancentred system design: First, it stresses the importance to consider individual differences in especially intelligence in order to enhance operator performance. A thorough literature review regarding human-centered system development research and interface design has demonstrated that the individual differences in intelligence have not yet been considered sufficiently although their consideration yields high potentialities in reducing the probability and severity of operator errors. The latter conclusion is based on research results about Ackerman's (1988) skill acquisition theory. Second, based on psychological diagnostics and especially the item response theory, a method has been proposed to allow the technical system to assess relevant abilities of its user based on the basis of

- the difficulty of everyday tasks,
- the person's reactions towards these tasks,
- and a function specifying the relationship between the person parameters, task parameters and the probability of correct or wrong responses to these given tasks.

An artificial neural network approach has been discussed as one possible method to automate the assessment. Third, guidelines for reconfiguring the system and/or the interface have been derived. Last, a hypothetical example has been introduced to stress the practical relevance of the proposed dependable system design methodology. The example made use of the Berlin intelligence structure model.

The described procedures can also be applied to assess other abilities, such as, e.g., the motor abilities of the operator.

Whether the proposed system design will work and actually meet the goal to enhance dependability will depend on the following:

- First, the artificial neural network needs to be trained with a representative set of person parameters.
- Second, the relevant ICC functions must be valid.
- Third, the solution of the task must depend on the measured abilities.
- Last, the reconfigurations of the system and/or the interface must ensure that the intelligences required operating both match the ones the human beings are most talented in.

Future work will aim at demonstrating that, if these prerequisites are given, the proposed system and interface design will actually have an impact on the overall dependability of the human-machine system. Further, the approach will be expanded to also cover other dependability-relevant abilities, such as working memory, attention or psychomotor abilities, which are more real time critical, as they are not as stable as is intelligence. It will demonstrate the impact of a very close and inter-disciplinary interaction between psychological diagnostics research, human factors research, dependability research, and automatic control.

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