Reducing Complexity with Simplicity - Usability Methods for Industry 4.0

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At RWTH Aachen University the research cluster "Production Technology for High-Wage Countries" engages in advancing the polylemma of production. In many cases engineers and physicists develop simulation tools, machine interfaces, and data exploration tools but lack essential training in Human-Computer Interaction. Without proper training the interaction of visual, cognitive and task complexity can lead to solutions that are valuable only to the developers themselves, but are not usable without extensive training. We show the most critical ergonomic factors for developing software in a scientific engineering setting that focuses on complex problems. We present an overview of usability methods as well as complexity reduction methods and their applicability in engineering software design. We present an exemplary study for the case of supply chain management, where the approaches were successfully integrated into a serious game not only serving as an investigatory tool but also as a training utility for supply chain managers.

Practitioner Summary: This overview aims to be used as an entry point for engineers interested in usability and its applicability from a simulations and visualizations point of view. Factors that create complexity and how they can be reduced are presented. Usability methods are evaluated in regard to their applicability.

Keywords: Complexity reduction, Qualitative Study, Industry 4.0, Usability, Internet of Things

1. Introduction

Industry 4.0 or the Internet of Things describes a paradigm shift in production technology. It refers to the shift of awareness and responsibility from the production process to the product itself. Every product component in the production process has an identity and instructs the machines what needs to be done to it and where it needs to be shipped. This shift enables processes that allow mass customization, production as a service, and feedback from products in the market (e.g. usage statistics, failures, required maintenance, etc.). In order to facilitate the full potential of industry 4.0 new processes and tools need to be developed, allowing innovative production processes. Often, existing processes either aim at scale effects using highly planned processes (i.e. lots of cheap identical products) or scope effects (i.e. very few expensive individual products). Combining these effects is a core dilemma in production.

At RWTH Aachen University the research cluster "Production Technology for High-Wage Countries" engages in advancing the so-called polylemma of production. Engineers from forty institutes collaborate on ensuring production in high-wage countries like Germany by addressing the scale-scope dilemma and the plan-value dilemma. Solution hypotheses include generative processes, additive manufacturing, self-optimization, technology integration, and data transparency (Brecher et al. 2012).

Many of the approaches used in the cluster of excellence combine planning and cybernetic methods (i.e. self-optimizing processes) in order to deal with the complexity of the fluctuating supply chains and fluctuating customer orders. The increasing demand for product quality under fluctuating quality of raw material makes intensive simulations necessary to create stable and reliable processes. These innovative processes can address product aspects in every phase of the production process-chain. They can work as early as in material design (e.g. metallurgy simulations for hot rolling, casting, annealing, carburizing & joining), manufacturing (e.g. laser cutting), assembly (e.g. robot-based large part handling, assembly of focusing lenses), or as late as in logistics management (e.g. shop-floor logistics, supply chain management). Most of these processes require human interaction with the system – either to interpret simulation data or to be the final decision maker in self-optimizing processes. Since the process data behind these interactions is often complex (i.e. large amount and highly connected) visualizations or decision support systems based on these

data easily become complex as well. The worker remains the most flexible component in this cyber-physical system and his interface becomes the key component of industry 4.0 settings (Gorecky et al. 2014). The rising field of Human-Computer Interaction in Knowledge Discovery in Databases (HCI-KDD, Holzinger 2013) plays a critical role when dealing with large amounts of multidimensional data and semi-structured data in a human understandable way.

2. Complexity in Human-Computer Interaction

Human beings interface with machines through various channels. Vision, hearing, and sometimes touch are used to communicate from machine to computer. Manual interaction, touch, voice, gesture, gaze, and sometimes even brain interfaces are used to communicate from human to machine (Kortum 2008). Nonetheless, these bottlenecks are only regarded as superficial from an HCI perspective. When looking at Big Data (i.e. large amounts of highly complex, multi-dimensional, highly unstructured data, e.g. medical records or logistics data) beyond these shallow interfaces, the communication between the deep interfaces must be addressed. Mapping from data to mental models (Johnson-Laird 1986, Calero Valdez et al. 2010) or understanding of data is far harder than optimizing user interface (UI) element placing. In order to understand how these problems should be addressed we first look at aspects of complexity that matter in designing a system.

2.1. Visual Complexity

Visual complexity refers to the complexity of information presented via the visual system. Early approaches to describe visual complexity stem from the field of Gestalt psychology (Köhler 1947) and try to describe the complexity of simple visual forms. Gestalt psychology bases on the *Prägnanz* law, which states that the organization of knowledge will converge to the best possible solution under any given condition. It aims at coding (not only) visual precepts with *maximum simplicity* or *maximum homogeneity* according to higher order variables in perception. The simplest explanation for any given set of percepts triumphs. Visual forms in particular are either represented as a set of single visual forms or as visual codes. The simplicity principle investigated by Hochberg (1957) demonstrated that forms change in memory according to their *Gestalt.* Defining differences in a relevant dimension are exaggerated while irrelevant differences diminish over time.

Later approaches to visual complexity often draw from the field of information theory, particularly from Shannon's information entropy (1948). The amount of information is measured by the deviance of the content from any random content. This means that forms that carry more information are more complex. In order to create complex forms more instructions are required than for simple forms. Experiments show that simpler forms are easier to learn (less information), while complex forms are easier to discriminate (more information). On the other hand, more complex forms require more reaction time in recognition tasks (Mavrides & Brown 1969).

J.J. Gibson (1979, cited from 2013) reframed visual complexity by integrating higher order invariants in perception. Often (algorithmically) seemingly more complex visual input can be integrated into a simpler explanation when all individual percepts support a unique perceptual hypothesis. The complexity of a given visual stimulus can thus change (in this case decrease) once a unifying interpretation of the sensory data is available (i.e. visual chunking). Suddenly the picture becomes clear and what was seen cannot be unseen.

When information needs to be conveyed, the given goal is often important in perceived visual complexity. Reaction times in one-dimensional search tasks (e.g. find the red O among green Os) are significantly faster than multi-dimensional search tasks (e.g. find the red O among green Os and red Xs). One dimensional visual search tasks often benefit from the *pop-out* effect (Treisman & Gelade 1980) allowing for parallel processing. The time for finding a single red X among green Xs is independent of the amount of green Xs in the visual array. This effect has been demonstrated for various dimensions of visual perception (e.g. line orientation, luminance, color, curvature, number, line intersection, figure closure, flicker, motion direction, lighting orientation) and can be learned for further dimensions by feedback training. An exhaustive review on visual complexity theory can be found by Donderi (2006).

2.2. Task Complexity

Even if the perception of visual inputs worked perfectly, the operations required for the perceived data could be complex. Task complexity has been found to influence performance and behavior (Liu & Li 2012). The ever-increasing complexity of tasks in ever-increasing dynamic settings, even when supported by

computerized tools, becomes increasingly problematic (Liu & Li 2011). Payne (1976) found that participants chose worse strategies when faced with tasks of higher complexity (i.e. multivariate decision making). Participants did not evaluate multivariate aspects, but chose to eliminate options according to singular aspects. The complexity of a task moderates the goal-setting effect (i.e. improved perceptual performance when a goal is set) and reduces the effect in complex task scenarios. Task complexity is assumed to influence mental workload (Jacko and Ward 1996) and thus reduce performance. Often task complexity is seen as an interaction of task, task performer, and task environment. Nonetheless, Liu and Li (2012) stress that task complexity (or objective task complexity) should be seen as different from task difficulty (subjective task difficulty, cf. Kieras & Polson 1985). They identify five components that contribute to task complexity. The g*oal or output* factor influences complexity as in more clarity and redundancy decrease complexity, while more, conflicting, and changing goal definitions increase task complexity. The *input* factors relate to stimuli and their influence on complexity. Again, clarity and redundancy decrease task complexity, while diversity, inaccuracy, conflict, unstructured guidance, and non-routine events increase task complexity. Additionally, a mismatch of cognitive and stimulus presentation increases task complexity. Interestingly, the quantity of stimuli shows a U-shaped influence on task complexity. Too little input is not helpful, too much is overwhelming. *Process* factors relate to the processes/paths that lead from input to output. Again, clarity reduces complexity as well as repetitiveness (i.e. training). Task complexity increases when many possible paths exist, which require many steps, if path interactions conflict, and when either cognitive of physical requirements for any action increase. *Time* factors increase complexity, whenever things have to be done concurrently or under time pressure. The *presentation* influences complexity in various ways (hence the section on visual complexity). Heterogeneity increases and compatibility decreases task complexity.

Liu and Li (2012) derived ten dimensions of complexity that all indicate high task complexity – size, variety, ambiguity, relationship, variability, unreliability, novelty, incongruity, action complexity, and temporal demand.

2.3.   Cognitive Complexity

Beyond these perceptional and task-related limitations cognitive limitations apply. Human beings have evolved to deal with the complexity of social relationships of small tribes like Machiavellian structures (hence Dunbar's Number, cf. Dunbar & Dunbar 1998). The necessities for cognitive complexity derive mostly from understanding social relationships (e.g. kinship, hierarchy, coalitions). This allows humans to effectively deal with relationships that are similar to these social relationships.

Human knowledge and reasoning can be seen as relational knowledge processing, which underlies its own limitations. Humans can process quaternary relations at maximum (Gross & Fox 2009, Halford et al. 2006). Simpler relations require less cognitive complexity. Relations are more suitable to human processing when they are transitive, symmetric or have a lower degree (e.g. unary or binary relations). Relations that are too complex are segmented (i.e. broken into smaller relations) and then processed sequentially and serially. If relations do require a higher degree, information can become lost in segmentation. Relation processing is important for planning tasks (Halford et al 1998), categorization of stimuli (Jameson & Gentner 2009), language processing (Andrews et al. 2006), and knowledge acquisition.

Typical for human intelligence is the autonoetic consciousness, allowing humans to see themselves in the past, present, and future. This allows planning, but has a bias for an over-allocation of resources in the future (future-me will have to deal with it), which needs to be considered when allowing multi-phasic time-deferred actions.

The concept of *narrative intelligence* was coined by Turner (1996). It assumes that humans are better at understanding something when it has a narrative to it. Stories are easier to understand. And some would even say, "[u]nderstanding narrativity is argued to be crucial to understanding human cognition" (Barett et al. 2007). A problem is that we also assume the intentional stance (Dennet 1989), expecting intentions behind occurrences out of a cognitive bias.

Uncertainty, which is always present in important situations, can influence how judgment is cast in situations where information is unavailable or possibly incomplete (Tversky & Kahneman 1974). Judgment is not cast according to *rational choice* but often according to cognitive biases. Most importantly, humans judge according to representativeness (how typical is this to my memory?), availability of instances (do I easily recall situations like this?), and adjustment from anchor (what did the last instance look like, even if unrelated?).

Good reviews on cognitive complexity can be found in Halford et al. (2010) on relational knowledge and in Barrett et al. (2007) on the influence of social complexity. Further cognitive limitations are not directly related to the primate origin of human beings. Among them we find limitations in attention span, differences in bottom-up/top-down understanding processes, time consumption in data interrogation processes, and the limitations of the visual sketchpad to 3D space dimension (at best).

2.4. Implications for Interface Design

The limitations derived from perception and cognition under the influence of task complexity should be addressed by an appropriate interface design. The interface should convey meaning by its design. Dimensions in data that are connected should be displayed in a connected fashion (e.g. width and height of a rectangle for value and trust in value of a variable, cf. Barnett & Wickens 1988) if they need to be evaluated as a conjoint variable. Pop-out of comparable dimensions by alignment (i.e. are lengths equal?) can be used to identify outliers directly and in parallel.

Still, in any given visualization we can only use so many dimensions in presenting data. When displaying data in a static fashion, the following dimensions can be modified: 2D-Position, size, opacity, color, and texture. Here, the *separability* (Lockhead 1966) of dimensions must be respected (e.g. hue and brightness are not separable), otherwise decoding of variables cannot be performed properly. Furthermore, one must consider that investigating multiple dimensions of this kind at once is still hard, especially when mapping of data is non-canonical.

According to Tufte & Graves-Morris (1983), the aim should always be to maximize the data-ink ratio, as in to present only primary information and to remove redundancy. They show how one can proceed to decrease the "lie-factor" in removing unnecessary chart-junk. This approach contradicts some of the findings in task-complexity. Redundancy in the input-component does reduce complexity, but only to a certain point. Finding the optimum presentation-task-fit is the challenge of the UI designer. Enriched displays that mimic the behavior of the underlying system (Pawlack & Vincente 1996) can help in decision-making under uncertainty, because they convey more meaning that minimalistic displays of raw data.

When visualizing dynamic data, additional usable dimensions are movement in space and changes in size, opacity, color, and blink. Adding to the complexity of multiple dimension interpretations, dynamic visualizations also limit the presentation period of an individual phenomenon. This exposes the presentation to further limitations of attention (e.g. attentional blink, color perception in the periphery, resolution difference in the fovea, movement sensitivity in the periphery, attention inhibition, etc.) (Lavie et al. 2004, Reeves et al. 1999, Cadiz et al. 2003, Cadiz et al. 2002).

When a task requires the analysis of e.g. 17 dimensions, the system should try to reduce to dimensions as much as possible. Only four items or dimensions can be investigated visually and be kept in working memory (Awh et al. 2007, Cowan 2001, Atkinson et al. 1976). The remaining four dimensions must be displayed in a fashion that enables the construction of the 17 dimension mental model from schemas that rely only on quaternary relations. This information chunking and compression can lead to generalization errors, or blindness on relationships between dimensions that are not displayed together or fall short due to segmentation.

Since knowledge can never simply be transferred, it must be communicated and often not in an immediate fashion. This process also underlies individual differences and thus human diversity must be considered when displaying complex data. Often engineers design systems that present problems only understandable by themselves. They assume what is easy for them, is easy for others (Kruger & Dunning 1999). This makes it extremely valuable to include end-users early in the design process.

3. Qualitative Survey

In the cluster of excellence we investigated how methods to reduce complexity and usability methods can be used to tackle the inherent problem of complexity. For this purpose we conducted interviews with researchers, how they approach complexity and usability and specifically addressed the topic of dimension reduction. Most engineers in our research cluster did not have formal training in usability. Often end-users are not available for testing. To accommodate for these peculiarities we evaluate usability methods in regard to their applicability in a setting like the cluster of excellence. The following subsections elaborate on our findings.

3.1. Methods to Reduce Complexity

In order to be able to visualize multidimensional data we can apply methods to simplify data and reduce complexity (Holzinger et al. 2012). The following approaches can be used:

- Dimension reduction: Filtering, statistical methods, folding, network graphics, Andrews curves, parallel axes visualizations (Calero Valdez et a. 2011, Calero Valdez et al. 2012, Spears 1999)
- Pattern detection - Low-pass-filter, Entropy detection (Holzinger et al. 2013, Holzinger et al. 2012, Mowshowitz & Dehmer 2012)
- Interaction methods - Rotation of data (3rd dimension), drill down, search, recommendation, browse, tool-tips, device rotation, game-based approaches
- Natural mapping of visualization and interaction methods (low-high, spatial to spatial, temperature to color, intensity to opacity, relatedness as closeness, zoom to pinch, select to tap, drag to move, tooltip-placement)

We found that matching the method to reduce complexity must match both domain knowledge of the future user and the available data. If complex mental models must be shaped during the interaction process, interrogative methods of interaction are helpful in acquiring a mental model.

Most applicable in scientific settings (e.g. simulation data presentation) are methods of dimension reduction and natural mapping methods. Methods of pattern detection are applicable in knowledge discovery tasks (e.g. collaborator finding). Complex interaction methods often require rich knowledge of programming and are often considered as a final "retouch" to programs. Therefore, simpler interaction methods are used more readily (e.g. search, drill down, fixed 90° rotation). These solutions are often not optimal and should therefore be evaluated in a usability context.

3.2. Usability Method Evaluation

We looked at selected usability methods (Courage & Baxter 2005, Holzinger 2005) that can be used in an engineering/scientific setting. As most engineers lack formal usability training, expertise is considered a negative factor for applicability here. Similar negative impact is found for methods that require multiple target users and are time consuming. We evaluate at usability inspection and test methods, as well as tools that can be used during the design phase (see Table 1). The required effort in *time* relates to the amount of preparation and expert time needed to conduct the method. *Costs* mean additional tools or hardware that needs to be acquired to adequately perform the method. *Utility* refers to the amount of possible defects and improvements that can be found during the method. *User* refers to whether or not end users take part in the process. Most methods can be applied in iterative design processes, which includes the user's tasks early in the design empirically and during use (Gould and Lewis 1985).

Table 1. Overview of Usability Methods and their Evaluation.

Name	Phase	Time Effort	Cost Effort	Utility	User	Applicability
Usability Heuristics	All	Low	Low	High	No	Medium
Cognitive Walkthrough	All	Medium	Low	High	Maybe	Low
Scenarios/Use-Cases	Concept	Low	Low	High	No	High
Paper Prototyping	Design	Low	Low	High	Yes	High
Clickable Prototyping	Design	Medium	Low	Medium	Yes	Medium
Participatory Design	Design	High	Low	High	Yes	Low
Focus Groups	Test	Medium	Low	Medium	Yes	Low
Interviews	Test	Medium	Low	Low	Yes	Low
Thinking Aloud	Test	High	Medium	High	Yes	Low
Web-Based User Tests	Test	Medium	High	High	Yes	Medium

4. Example: Logistics Game

To illustrate the benefits of the presented usability engineering methods we exemplify the successful development process of a business simulation game with the learning objective of conveying supply chain, material disposition, and quality management techniques. We originated from a System Dynamics model

(Forrester 1977) that incorporates supply chain management with quality management aspects and serves as a simplification of the complex interrelationships of today's production networks (Stiller et al. 2014).

For the design of the game interface, we first created a series of non-functional *paper prototypes* with different spatial layouts and varying information complexity. Through several iterations a visual interface evolved that followed the principles of the Gestalt psychology and divided the complexity of the tasks in the game in several distinct visual chunks (see Fig. 1, left). Next, a low fidelity functional prototype was realized in a spreadsheet application to identify suitable game parameters (e.g., cost functions) with an adequate level of task complexity, and to validate the soundness of the game with domain experts (see Fig. 1, center). Based on these findings the game was realized as a web application (see Fig. 1, right) and a *Web-Based User Tests* showed that interacting with this learning environment raises the awareness for quality management issues and that people learned to successfully handle the complexity of the simulated model of a production network (Philipsen et al. 2014a). The final web-based business simulation game was again submitted to usability evaluations using the *think aloud* method and *expert interviews*. The interface was further optimized based on this feedback by harnessing the *pop out* effect through highlighted Key Performance Indicators and task-oriented spatial layouts. A final *Web-Based User Tests* in conjunction with an *AB-test* compared the original with the refined interface: The participants found the new interface easier to use and higher profits and higher product quality was achieved with final iteration of the game's interface, indicating a higher effectiveness and better learning outcomes based on increased usability of the application (Philipsen et al. 2014b).

Besides being a suitable learning environment to facilitate the understanding of the interrelationships of modern production networks the environment can further be used to empirically evaluate the influence of task and interface difficulty (Mittelstädt et al. in press) and how this complexity can successfully be reduced (Brauner et al. 2013). For example, aspects of the simulated production network can be controlled and manipulated and the influence of different visualizations in relationship with aspects of user diversity can be investigated in relationship with the achieved game performance.
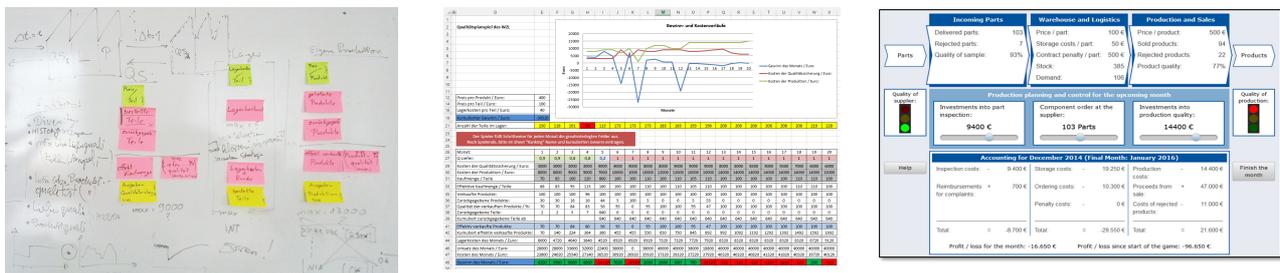
Fig. 1. Development stages of the business simulation game (*left* paper prototype, *center* functional prototype in a spreadsheet application, *right* functional web-based application).

5. Discussion

Applying not only adequate visualizations but also interaction mechanisms is crucial for exploring data. Depending on the type of data different approaches are either more feasible or more useful. One must carefully evaluate how to include both the user and the data expert in early phases of the system design. Integrating user requirements from a use case point of view and their feedback on early prototypes is helpful in designing a system that is helpful in decision-making and addresses complexity accordingly. Creating a design space of data visualization and interaction patterns will be helpful for further endeavors. Further work in this area is required and evaluations are necessary. In particular, applying findings in real-life settings with fluctuating motivation, environment and changing goals could lead to drastically different results.

Beyond an improvement of processes in usability and dimension reduction, individual factors will play an increasingly important role in the future of work, as user diversity factors like age (Ziefle & Bay 2005) influence how users deal with complexity. Changes in requirements caused by Industry 4.0 (e.g. increased flexibility, more diverse tasks, higher order decision making) will stress the importance of good usability and ergonomics in scientific and industrial settings. This is specifically true in face of a change in demography, changing values and a globally connected world.

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