TASK COMPLEXITY IN INDIVIDUAL STOCK CONTROL TASKS FOR LABORATORY EXPERIMENTS ON HUMAN UNDERSTANDING OF DYNAMIC SYSTEMS

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ABSTRACT

Dynamic stock control tasks have been frequently used in laboratory experiments in behavioral research to investigate understanding of dynamic systems. System dynamics modeling has regularly been used as a method to design such simulation based stock control tasks. Studies applying these simulations are almost exclusively focused on how the structure of a system (represented in the form of the simulation model) affects human's inference of system behavior. In doing so, these studies hardly ever take into account that dynamic stock control tasks possess also other forms of complexity than 'just' the complexity of the underlying system structures. The concept of 'task complexity' is nothing new, but its application to research on human understanding of dynamic systems using stock control tasks and applying system dynamics modeling remains virtually absent. Hence, the objective of this paper is to carve out what task complexity entails when applied to dynamic stock control tasks in order to determine its usefulness for future research on human understanding of such tasks. In this paper, task complexity is conceptualized consisting of ten complexity dimensions: 1) size, 2) variety, 3) redundancy, 4) ambiguity, 5) variability, 6) unreliability, 7) novelty, 8) incongruity, 9) connectivity, and 10) temporal demand.

KEY WORDS: Task complexity, dynamic stock control task, dynamic decision task, laboratory experiment, human understanding, task model, task complexity dimensions, conceptualization, simulation model.

1. INTRODUCTION

Dynamic stock control tasks have been frequently used in laboratory experiments in behavioral research to illustrate poor human understanding of dynamic systems (Gonzalez & Dutt, 2011). Dynamic stock control tasks are a specific type of dynamic decision tasks. Decision tasks are dynamic whenever decisions made at time *t* alter the state of the system and thus the information that condition decisions to be made at time *t+1*. In fact, the decision maker and the system are entwined in feedback loops whereby decisions alter the state of the system, giving rise to new information and leading to new decisions (Diehl & Sterman, 1995: 198). More specifically, in dynamic stock control tasks, people need to balance (an) accumulation(s), or increase or decrease (an) accumulation(s) towards (a) predefined goal(s), by making repeated decisions about the inflow(s) and/or outflow(s) through which the accumulation(s) is/are allowed to vary. In order to make these decisions, participants receive information feedback about their decisions' outcomes in each time period (Gonzalez & Dutt, 2011: 1905). Important is that the accumulation(s) and flow(s) might also be part of a larger system determining the rates of change affecting the accumulation(s). The assumption underlying these tasks is that when participants are able to balance the accumulation(s), or increase or decrease (an) accumulation(s) towards (a) predefined goal(s), they also understand the dynamic system which alters the accumulation(s).

In order to create such dynamic stock control tasks, system dynamics modeling has frequently been used as a method to develop computer simulation models that capture the dynamic behavior of accumulations and their flows (e.g., Atkins, Wood, & Rutgers, 2002; Diehl & Sterman, 1995; Gonzalez & Dutt, 2011; Özgün & Barlas, 2012; Yasarcan, 2010, 2011). User-interfaces allow task performers to interact with these computer simulation models through making decisions and receiving information feedback about the outcome of their implemented decisions on the state of the accumulations. Researchers that have applied these computer simulation models as dynamic stock control tasks discovered that people have difficulties with balancing the accumulation(s) or increase or decrease (an) accumulation(s) towards (a) predefined goal(s). They state that this is especially true for system structures containing 1) strong feedbacks (e.g., Diehl & Sterman, 1995; Diehl, 1989; Langley, Paich, & Sterman, 1998; Paich & Sterman, 1993; Young, Chen, Wang, & Chen, 1997); 2) non-linear relationships between variables (e.g., Paich & Sterman, 1993; Sterman, 1989a; Sterman, 1989b); and 3) significant time delays between action and response or in the reporting of information (e.g., Arango, 2006; Barlas & Özevin, 2004; Broadbent & Aston, 1978; Diehl & Sterman, 1995; Diehl, 1989; Sterman, 1989b). As a result, these researchers conclude that people have difficulties inferring system behavior from system structure because 1) humans have limited cognitive abilities to capture the complexity of dynamic systems (e.g., misperceptions of feedback; Sterman, 1989a; Sterman, 1989b); and 2) humans apply erroneously (simple) decision heuristics when managing complex systems (e.g., correlation heuristic; Cronin, Gonzalez, & Sterman, 2009).

However, an important limitation of the above-mentioned studies is their almost exclusive focus on how the structure of a system (represented in the form of a simulation model) affects human's inference of system behavior. Let's illustrate this by looking at an dynamic stock control task recently published by Gonzalez & Dutt (2011) as a task that can be used for behavioral research on human understanding of dynamic systems. Their neatly designed task consists of an accumulation which changes over time solely based on two inflows and two outflows. One of each is within the task performers direct control (i.e., decision variables) and one of each is an exogenously defined environmental inflow and outflow, respectively. Hence, the mathematical formalization of the model is fairly simple and is given by equation (1).

$$\begin{aligned} Accumulation_t = {} & Accumulation_{t-1} \\ & + (User\ Inflow_t + Environmental\ Inflow_t - User\ Outflow_t \\ & - Environmental\ Outflow_t)DT \end{aligned} \tag{1}$$

The objective of the task is to increase the two gallons of water that are initially in the accumulation to four and keep it at that level afterwards. In order to achieve this, an user-interface with a visual representation of the task and information requirements is provided to the task performer as illustrated in figure 1.

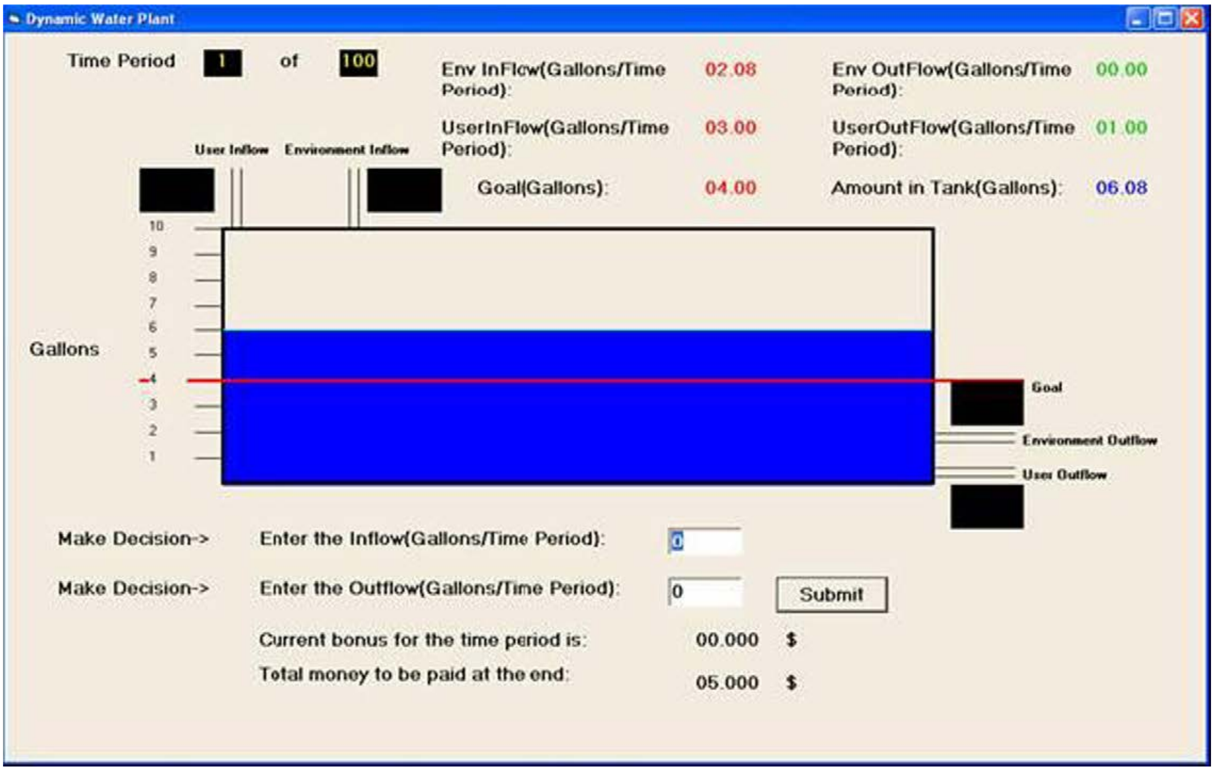

Figure 1: User-interface of Gonzalez & Dutt's (2011) generic dynamic control task

Research on human understanding of dynamic systems would, like Gonzalez & Dutt (2011), use this dynamic stock control task (or similar tasks like, for instance, the beer game, fish banks, etc.) mainly to investigate how changes in the structure of the system (for instance, changes in the equations behind the environmental inflow and outflow) affect human's inference of the behavior of the accumulation. In doing so, these studies hardly ever take into account that such tasks are more complex than 'just' the complexity of the underlying stock-and-flow structure. There is also, for instance, the way in which the task is presented to the task performer and the process by which the task performer needs to perform the task. For instance, in Gonzalez & Dutt's (2011) study, the procedure was organized in such a way that task instructions were given to the task performers on the computer before engaging in the task. Participants were encouraged to ask questions after reading the instructions and were also handed a paper copy of the instructions. Participants were not given any information concerning the nature of the environmental inflow and outflow, and were told that these environmental flows were outside their control over the entire course of the task. They were asked to control the accumulation for 100 time periods which completed the task.

The importance of these 'other task characteristics' was recently vividly illustrated by Fischer & Degen (2012) who showed that task characteristics, like the form of the task, can improve human's understanding of 'simple' stock-and-flow behavior. Their study clearly shows that if we aim at studying human's understanding of dynamic systems through tasks, we need to look at the complexity of the entire task instead of just the dynamic system underlying the task. The idea of looking at 'task complexity' more holistically is nothing new as the first important attempt of defining the construct dates back to the mid of the 1980s (e.g., Wood, 1986). Nevertheless, its application to research on human understanding of dynamic systems using stock control tasks based on system dynamics modeling remains virtually absent. As such, the objective of this paper is to make a first attempt at carving out what task complexity entails when applied to dynamic stock control tasks in order to determine its usefulness for future research on human understanding of such tasks. Consequently, the research question for this paper is: What is task complexity in the context of dynamic stock control tasks? To be explicit, dynamic stock control tasks are, given this paper's context of laboratory experiments in decision making research, tasks that contain a simulation model as a substitute for the real system that needs to be controlled. We also want to stress that this paper is limited to the conceptualization of task complexity only. The authors believe that sufficient attention should be devoted to the conceptualization of this multidimensional construct in order to pave the way for an operationalization and measure of task complexity in the context of dynamic stock control tasks[1].

In order to address our research question, this paper starts by illustrating the existence of two approaches for defining task complexity: an objective approach and a subjective approach. The objective approach, basically, defines task complexity as a property of the task and independent of task performers, whereas the subjective approach considers task complexity as a conjunct property of task and task performer characteristics. Next, we give an argumentation of why the objective approach is chosen as most suited given the experimental laboratory context of this study. In addition, we also clearly state that objective task complexity cannot be an intrinsic property of a task per se because tasks entail inevitably subjective aspects as they are created by a creator and observed by an observer. Objective task complexity should therefore be defined more precisely as an intrinsic property of a task model where a task model is an inter-subjectively agreed-on, simplified, prototypical representation of the task (Liu & Li, 2012: 558). The objectivity of this redefinition of task complexity is embodied in the fact that the task model allows for manipulation and quantitative assessment of task complexity. In the next section, this paper continues by objectively defining what a task is and puts forth a task model representing dynamic stock control tasks. This task model provides the key to defining objective task complexity which consists of ten complexity dimensions: 1) size, 2) variety, 3) redundancy, 4) ambiguity, 5) variability, 6) unreliability, 7) novelty, 8) incongruity, 9) connectivity, and 10) temporal demand. In the discussion section, this 'new' conceptualization of task complexity is subsequently compared and linked to the following already known complexity concepts: 1) system complexity, 2) detail complexity, 3) dynamic complexity, 4) structural complexity, and 5) social complexity. The discussion section also highlights the value of our conceptualization of task complexity for future research on human understanding of dynamic systems. This paper ends with a conclusion that briefly summarizes this 'new' conceptualization of task complexity and its potential for future research.

2. APPROACHES IN DEFINING TASK COMPLEXITY

Task complexity is one among the many concepts that lack a general and widely-accepted definition. The reason being that task complexity is defined differently across various domains and even within the same domain. In addition, different types of tasks often also have their own definitions and

[1] The following reference might be interesting for those interested in this next step of operationalizing and measuring task complexity: Liu, P., & Li, Z. 2014. Comparison of task complexity measures for emergency operating procedures: Convergent validity and predictive validity. ***Reliability Engineering & System Safety***, 121(0): 289-293.

operationalization of task complexity. However, the variety of definitions that exist fall within two broad approaches: the objective approach versus the subjective approach (Liu & Li, 2011, 2012; Rouse & Rouse, 1979).

Proponents of the objective approach consider task complexity to be directly related to task characteristics and independent of task performers. In general, two distinct views can be identified within the objective approach. The first is the structuralist view which defines task complexity from the structure of a task. Task complexity can in this view, for example, be defined as a function of the number of elements of which the task is composed and the relationships between those elements (Liu & Li, 2012). Wood (1986), Campbell (1988), Bonner (1994), and Ham et al. (2012) are some examples of existing conceptualizations of task complexity belonging to this view. The second view within the objective approach is the resource requirement view which defines task complexity as resource requirements imposed by a task. Basically, any task characteristic that influences the resource requirements placed on task performers can be within the idea of task complexity (Liu & Li, 2012). In this view, the concept of resource represents the resources in human information processing, such as visual, auditory, cognitive, and psychomotor resources (McCracken & Aldrich, 1984), but also knowledge (Gill, 1996; Kieras & Polson, 1985), skills (Byström, 1999), and even time (Nembhard & Osothsilp, 2002). The idea is that task performers are required to invest more resources during task performance for more complex tasks.

Next, proponents of the subjective perspective consider task complexity as a conjunct property of task and task performer characteristics. When the complexity of the task outruns the capacity of the task performer, the task performer will perceive the task as complex. In the subjective approach, complexity sometimes becomes a 'state of mind' affecting the way the task performer performs the task (Liu & Li, 2012: 557). Hence, task complexity is, in this approach, the complexity perceived by the task performer. It is therefore also often referred to as perceived (e.g, Marshall & Byrd, 1998; Te'eni, 1989), or experienced complexity (e.g., Campbell, 1988). Task complexity is in this approach a relative term (Gonzalez, Vanyukov, & Martin, 2005). The interaction view on task complexity applies this subjective definition of task complexity as it is the only view who defines task complexity as a product of the interaction between task and task performer characteristics (Liu & Li, 2012: 555). Studies that have used this interaction view to conceptualize task complexity are, for example, Byström & Järvelin (1995) and Vakkari (1999).

Of course, both the objective and the subjective approach to defining task complexity have strengths and weaknesses. However, Liu & Li (2012) identify two serious problems when defining task complexity subjectively which makes this approach unsuitable for the purposes of this study. First, since subjective task complexity mixes the effects of task, task performer, and environment, it makes it hard, if not impossible, to generalize findings across tasks. Second, subjective task complexity makes it impossible to distinguish between the complexity of a task and its difficulty. Both problems are overcome when defining task complexity objectively. However, the classic ways of defining task complexity from the structure of a task or the resource requirements imposed by a task has recently been criticized by Liu & Li (2012). They convincingly point out that objective task complexity cannot be an intrinsic property of a task per se because tasks entail inevitably subjective aspects as they are created by a creator and observed by an observer. Objective task complexity should therefore be defined more precisely as an intrinsic property of a task model where a task model is an inter-subjectively agreed-on, simplified, prototypical representation of the task (Liu & Li, 2012: 558). The objectivity of this redefinition of task complexity is embodied in the fact that the task model allows for manipulation and quantitative assessment of task complexity. Hence, this redefinition does not mix the effects of the task, task performer, and environment and it also allows for distinguishing between task complexity and task difficulty. Task complexity is then defined as a function of the objective characteristics of the task model that represent the task, whereas task difficulty involves the interaction among task, task performer, and context characteristics. In general, task difficulty refers to the extent to which task performers perceive difficulty in performing a task.

Given the fact that this paper's focus is on laboratory experiments and given the fact that Liu & Li's (2012) redefinition of the task complexity concept allows for manipulation and quantitative assessment, this study opts to apply Liu & Li's (2012) conceptualization of task complexity and investigates how it usefully can be employed in the context of dynamic stock control tasks. This implies that in the remainder of this paper we follow the objective approach in defining task complexity according to Liu & Li's (2012) abovementioned objective definition of task complexity as the intrinsic property of a task model.

3. TASK AND TASK MODEL

In order to explain what a task model is, we first need to agree on what a task is as there is in the literature limited consensus on the understanding of a task and its characteristics (Hackman, 1969; Liu & Li, 2012; Wood, 1986). Back in the 1960s, Hackman (1969) identified four approaches to defining task. The first approach is labeled 'task qua task' and defines tasks in terms of 'objective' properties of tasks. The second approach is referred to as 'task as behavior requirement' and defines tasks based on the response a subject should emit in order to achieve some criterion of success given the stimulus situation. The third approach defines task as a behavior description and focuses on the response the performer actually does (and not should) emit, given the stimulus condition. Finally, the 'task as ability requirement'-approach defines tasks by involving specification of the patterns of personal abilities or characteristics required for successful task completion.

Based on his conceptualization, Hackman (1969) proposed that a definition of a task for the behavioral sciences should follow an objective approach, or what he referred to as the 'task qua task'-approach. His reasons for this choice were quite similar to the above-mentioned reasons for choosing the objective approach above the subjective approach when defining task complexity. Hackman (1969) even explicitly stated that the 'task qua task'-approach allows for precise operational specification and it is also the only approach which defines a task completely independently of the behavior to which it is expected to relate. Hackman's (1969: 113) objective definition of a task is still widely used in research and reads as follows: "a task may be assigned to a person (or group) by an external agent or may be self-generated. It consist of a stimulus complex and a set of instructions which specify what is to be done vis a vis the stimuli. The instructions indicate what operations are to be performed by the subject(s) with respect to the stimuli and/or what goal is to be achieved". Hackman's objective approach in defining a task links very well with the objective approach in defining task complexity and is therefore in this paper used as a steppingstone for designing a model of task.

Earlier in this paper, a task model was defined as an inter-subjectively agreed-on, simplified, prototypical representation of the task. We now add to this that such a representation is a configuration of different task components. Hackman's (1969) definition of a task contains four classes of objective task components: 1) stimuli, 2) instructions, 3) operations, and 4) goals. Hackman's (1969) definition together with other classic definitions and models of tasks (e.g., Bonner, 1994; Farina & Wheaton, 1971; Li & Belkin, 2008; Wood, 1986) were recently extensively reviewed by Liu & Li (2012) in order to identify generic classes of objective task components. Their review concluded with identifying the following six generic classes of objective task components: 1) goal, 2) input, 3) process, 4) output, 5) time, and 6) presentation. Figure 2 illustrates how a task model of a dynamic stock control task based on a simulation model is created based on these generic task components supplemented with the new generic task component of the simulation model itself.

In this model, 'goal' and 'input' serve as the prerequisites of the process required to generate a task output. In general, a goal is defined as a desired output which may complete the task or a desired state which may be used to compare the output of the task against. In the case of dynamic stock control tasks, the last definition is more appropriate since the goal is to balance (an) accumulation(s), or increase or decrease (an) accumulation(s) towards (a) predefined goal(s). The output of a task is compared to the goal(s). Inputs in this model aggregate the collection of information cues, stimuli, data, procedures, guidance, instructions and random events at the beginning and during the performance of the task. Next, the process of the task can, in general, be defined in terms of paths, steps, actions, and operations needed to perform the task. Crucial in the process of performing dynamic stock control tasks is that task performers need to make decisions about the inflow(s) and/or outflow(s) through which the accumulation(s), as part of the stock-and-flow structure represented by the computer simulation model, is allowed to vary. Hence, there is an interaction between the process and the simulation model that needs to be managed. This is represented in the task model by a double headed arrow between 'process' and 'simulation model'. The process of a task is also affected by the temporal dimension of the task where time itself might in turn be determined by the goal definition of the task (e.g., balance the accumulation as quickly as possible). Eventually, decisions will be implemented in the simulation model generating task output. The latter refers to the product or outcome of the task process, which in the case of dynamic stock control tasks become effective via the simulation model. In turn, the output of the task in a dynamic control task (might) serve as or affect input and/or the goal of the next iteration of this repeated decisions making process. Output can affect the goal through the process of goal adaptation (Lant, 1992) which result in 'floating goals' (Senge, 1990; Sterman, 2000). Goals might for instance errode in order to reduce cognitive dissonance (Festinger, 1957). Finally, the last task component is 'presentation' which refers to the fact that 'goal', 'input' and 'output' are presented to the person performing the task in order to initiate or affect the task. Presenting these task components might be done in various ways/formats. Hence, presentation is about how the content of these task components are made available to the task performer.

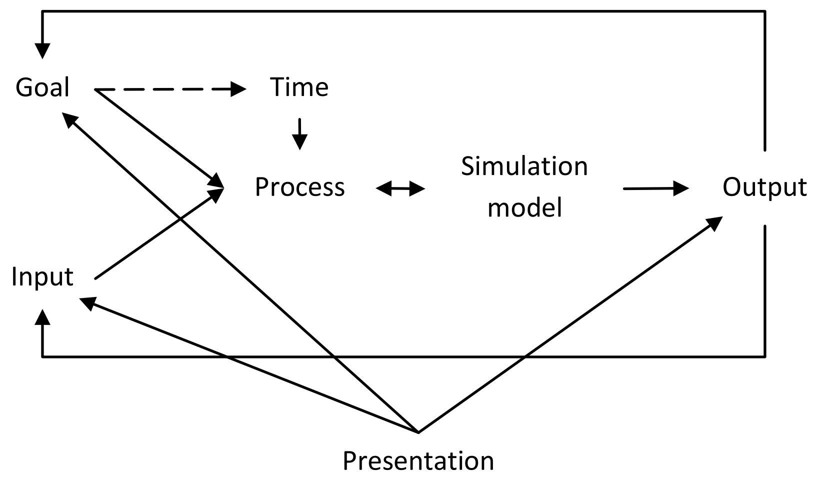

Figure 2: Generic task model of a dynamic stock control task based on a simulation model

4. TASK COMPLEXITY IN INDIVIDUAL DYNAMIC STOCK CONTROL TASKS

As objective task complexity is an intrinsic property of a task model, the next step is to derive task complexity from the task model developed in Figure 2. This is accomplished through introducing complexity contributory factors which are factors making a task complex or an indicator showing that the task is complex (Liu & Li, 2012). Complexity contributory factors are factors related to the task components of a task model. These factors can therefore be used to describe and differentiate tasks as well as task complexity among tasks. As these complexity contributory factors can be summarized into logical sets of task complexity dimensions, they provide the bridge between the task model and objective task complexity. The collection of these complexity dimensions is by Liu & Li's (2012) refered to as a task complexity model in which each dimension consists of several complexity factors that characterize task complexity in more detail.

Table 1 is a matrix illustrating how the different classes of task components of the task model (represented in the first two rows of the matrix) are linked to the different complexity dimensions of the task complexity model for dynamic stock control tasks (represented in the first two columns of the matrix) by means of the complexity contributory factors (represented in the remaining cells of the matrix). The content of this matrix is mainly a translation and extension of Liu & Li's (2012) review and 'generic conceptualization' of task complexity towards the context of dynamic stock control tasks. In doing so, an effort was made to stay as close as possible to their original conceptualization of task complexity allowing for constructively increasing the body of knowledge on task complexity. As a result, our matrix consists of ten complexity dimensions: 1) size, 2) variety, 3) redundancy, 4) ambiguity, 5) variability, 6) unreliability, 7) novelty, 8) incongruity, 9) connectivity, and 10) temporal demand.

Table 1: Task complexity matrix linking the task model to the task complexity model

		Task model						
	Task → Component Class Complexity dimensions ↓	Goal	Input	Process	Simulation Model	Output	Presentation	Time
Task complexity model	Size	• Quantity	• Quantity	• Quantity (of actions / steps / paths / decisions)	• Quantity (of variables / relationships / equations)	• Quantity		
	Variety	• Diversity	• Diversity	• Diversity (of actions / steps / paths / decisions)	• Diversity (of variables / relationships / equations)	• Diversity	• Heterogeneity in presentation format	
	Redundancy	• Redundancy	• Redundancy	• Redundancy	• Redundancy	• Redundancy		
	Ambiguity	• Clarity • Structure	• Clarity • Structure			• Clarity • Structure	• Clarity • Structure	
	Variability	• Rate of change	• Rate of change • Random events		• Robustness • Stochasticity	• Rate of change		
	Unreliability	• Inaccuracy	• Inaccuracy		• Technical correctness	• Inaccuracy		
	Novelty		• Non-routine events	• Repetitiveness			• Non-routine presentation formats	
	Incongruity	• Conflict • Mismatch	• Conflict • Mismatch	• Conflict • Mismatch	• Conflict • Mismatch	• Conflict • Mismatch	• Compatibility	
	Connectivity				• Interrelatedness of variables			
	Temporal demand							• Time availability • Concurrency

The size of a dynamic stock control task is defined in terms of the quantity of task components for the following classes: 1) goal: the number of goals; 2) input: the amount of input in terms of information and stimuli; 3) process: the number of actions, steps, paths (i.e., paths to arrive at 'solution'), and decisions; 4) simulation model: the number of variables, relationships between these variables, and equations; and 5) output: the amount of output in terms of information and stimuli.

Variety is defined as the heterogeneity in task components and applies to the following classes of task components: 1) goal: the diversity of goals; 2) input: the diversity of information and stimuli; 3) process: the diversity of actions, steps, paths, and decisions; 4) simulation model: the diversity of variables, relationships between these variables, and equations; 5) output: the diversity of output information and stimuli; and 6) presentation: the heterogeneity in terms of simultaneous or successive presentation of information and stimuli (Das, Kirby, & Jarman, 1975).

Redundancy captures the needlessness of (parts of) task components embedded in the task. Redundancy applies to input, output, goal, process, and simulation model. Redundancy in the input or output can, for instance, emerge when more input or output is given than necessary to understand and fulfill the task, or when input or output are unnecessarily repeated multiple times. Redundancy in the process can happen when actions, steps, paths, and decisions are unnecessarily taken in order to perform the task. Finally, the simulation model (mirroring a stock control system that needs to be managed) might have a lot of variables and relationships that do not contribute to the core dynamics of the model. Hence, redundancy in a simulation model occurs when not the entire model structure is necessary to capture the models core dynamics.

Ambiguity refers to the degree of clarity of the input, goal, output, and presentation. For input, goal, and output, clarity has mainly to do with completeness and specificity or precision. Precision concerns the fineness of distinctions made between the attributes that compose variables/factors

(Babbie, 2013: 188). Being precise leads to being specific. Besides completeness, specificity and precision, clarity has also to do with the amount of structure in the content of the input, goal, and output of the task. For instance, the level of structure attributed to the content of the task instructions and guidance (e.g., structured versus unstructured guidance). For presentation, clarity is about the choice of presentation format (e.g., tabular or grafical) and the level of structure attributed to the presentation format.

Variability refers to changes in or unstable characteristics of task components over time. In dynamic stock control tasks variability is mainly observed in the rate of change of input, goal and output as the output of the task at time *t* serve as or can affect the input and/or the goal of the task for the next iteration of the task, which in turn leads to changes in output. This dimension also covers random events in the input (e.g., noise) and robustness (i.e., the ability of a simulation model to resist change under a wide range of 'unusual' conditions that stress its designers' assumptions) and the level of stochasticity of the simulation model.

Unreliability is specified as the inaccuracy of input, goal(s), output, and simulation model. Accuracy is about reflecting the real world and should not be confused with precision or specificity (see the Ambiguity-dimension). Babbie (2013: 188) explains this distinction well with the following example: "Describing someone as "born in New England" is less specific than "born in Stowe, Vermont" – but suppose the person in question was actually born in Boston. The less-specific description, in this instance, is more accurate, a better reflection of the real world" Hence, inaccuracy has to do with misleading information/stimuli which is a common artifact of complex tasks based on (a) complex system(s) (i.e., in this case captured in a simulation model). Inaccuracy of the simulation model has to do with the internal validity of the model. Although the internal valididty of a simulation model can only be assessed subjectively in the context of the purpose for which the model is designed, the technical correctness of the model, as part of the internal valididty construct, can however be assessed objectively.

Novelty refers to the appearance of novel, irregular and non-routine events/actions or presentation formats within the task. This dimension mainly relates to the repetitiveness within the process of accomplishing the task, but it also captures the possibility of new input entering the task process through the appearance of non-routine events. It needs to be stressed that novelty has in this conceptualization nothing to do with the novelty of the task for the task performer as this would not fit the objective approach to defining task complexity to which we have committed ourselfs. Novelty is distinct from variety as, for instance, a high diversity of actions might still be repetitive if they, for instance, always follow the same sequence throughout the iterations required to accomplish the task.

Incongruity is defined as the inconsistency, mismatch, and incompatibility of task components. Incongruity can be attributed to task components if they do not fit with the other task components within or across classes of task components. Incongruity applies to all classes of task components except for time. Three types of complexity contributory factors are distinguished here: 1) mismatch, 2) conflict, and 3) compatability. Mismatch is distinct from conflict as mismatch does not necessary imply conflict. The instructions of the task might, for instance, not perfectly match the process. Nevertheless, this does not imply that they conflict. On the other hand, goals, for instance, might conflict amongst each other when attaining one goal negates or subverts attaining another (Locke, Saari, Shaw, & Latham, 1981). Finally, incongruence in the presentation can emerge if the presentation format is not adapted to other task components. For instance, presenting 'behavior over time' as input to a task verbally in the form of a narrative can be less compatible than presenting it in an actual graphical representation.

Connectivity is a term borrowed from Milling (2002) and refers to the interrelateness of a system. Hence, this dimension only applies to the simulation model. A proxy for the interrelateness of the simulation model could simply be the amount of relations over the amount of variables. More elaborate measures could take the strenght of the relationshsips into account.

Temporal demand is specified as time availability or concurrency between tasks and/or presentations imbedded in the task. This dimension is therefore exclusively linked to the task component of time.

5. DISCUSSION

This discussion section will mainly illustrate how this 'new' conceptualization of task complexity relates to already existing complexity concepts within the scope of dynamic stock control tasks. These complexity concepts are: 1) system complexity, 2) detail complexity, 3) dynamic complexity, 4) structural complexity, and 5) social complexity. Throughout this paper, we made clear that the complexity of a dynamic stock control task is more than just the complexity of the underlying stock control system (in this case formalized in the form of a simulation model). This brings us to discussing what system complexity is and how it links with task complexity.

Stock control systems are complex systems and the many definitions of complex systems mainly boil down to the idea of systems with multiple elements adapting and reacting to the pattern of multiple interactions these elements create (e.g., Arthur, 1999; Rind, 1999). Given this definition scholars regularly distinguish between detail complexity and dynamic complexity (e.g., Bozarth, Warsing, Flynn, & Flynn, 2009; Senge, 1990; Sterman, 2000). In the light of this definition, detail complexity of a system is about the multiple elements and the multiple relationships, whereas dynamic complexity has to do with the interactions between these elements.

To be more precise, detail complexity of a system is about the distinct number of components, parts, (interdependent) variables, or relationships that make up a system (Bozarth et al., 2009; Dörner, 1997; Senge, 1990). Detail complexity is the type of complexity most people think about when talking about complexity. Besides the fact that detail complexity is mainly used to refer to complexity in systems, detail complexity is also identified within tasks but often under a different label. Sterman (2000: 21), for instance, applies the term combinatorial complexity to refer to detail complexity which lies in finding the best solution out of an astronomical number of possibilities. Wood (1986: 66) uses the term component complexity which is a direct function of "the number of distinct acts that need to be executed in the performance of the task and the number of distinct information cues that must be processed in the performance of those acts". In sum, detail complexity, whether it be detail system complexity or detail task complexity, deals with 'quantity of elements' and is captured in the complexity dimension called 'size'. In this sense, detail system complexity in dynamic stock control tasks relates to the stock control system which is captured by the simulation model.

Where detail complexity is relatively straightforward to grasp, dynamic complexity is not. This clearly comes about when investigating the variety of ways in which scholars have attempted to define this concept. A first and commonly used way to define dynamic complexity is through specifying which structural components a system needs to have in order to be able to generate dynamically complex behavior. These structural components seems to be multiple feedbacks, time delays, nonlinearities, and accumulations (Langley & Morecroft, 2004; Sterman, 1994). However, this type of definitions do not describe what dynamic complexity is as it only describes what dynamically complex systems are. A second way defines dynamic complexity subjectively as complexity in which a system's response to a given set of inputs are not obvious or unpredictable (e.g., Bozarth et al., 2009; Senge, 1990). Dynamic complexity is defined subjectively in this case which does not align with the objective approach of defining concepts we set out to achieve in this paper. Finally, a third way of defining dynamic complexity is to refer to the non-stationary nature of the parameter values for the relationships between (state) variables, elements, and/or task components (e.g., Wood, 1986). Given this last and objective definition, dynamic complexity is captured in the task complexity dimension called 'variability'.

Structural complexity refers to the degree to which a task is performed using task specific knowledge, operators, and goals (Gill, 2008: 254). Structural complexity is not a property of the task itself but of the problem space used to perform the task, where a problem space is a representation of the cognitive system that will be used to perform a task described in terms of (1) a set of states of knowledge, (2) operators for changing one state into another, (3) constraints on applying operators, and (4) control knowledge for deciding what knowledge to apply next" (Card, Moran, & Newell, 1983: 87). Hence, following this structural complexity definition, low structure (e.g., unfamiliar tasks) is more complex than high structure (e.g., routine tasks). Structural complexity is not included in our conceptualization of task complexity as it is defined as an interaction between the performer's problem space and the particular task being performed. Hence, structural complexity is defined subjectively and refers to a performer's mental models (Gill & Cohen, 2008) which may vary significantly across task performers.

Finally, social complexity (often also referred to as behavioral complexity) characterizes the extent to which there is diversity in the aspirations, mental models, and values of decision makers (Roth & Senge, 1996: 93). Vennix (1996) points out that this diversity is a result of peoples continuous striving for the creation of reality. As people might perceive the reality only partially though selective perception, mental models of the reality will be social and partial representations of that reality. As this paper only conceptualizes task complexity for individual dynamic stock control tasks, social complexity is not considered in our conceptualization. Future research could extend this task conceptualization toward dynamic stock control tasks for groups. Doings so will probably need the inclusion of complexity dimensions capturing the social complexity construct.

Besides the fact that this paper only looks at task complexity of dynamic stock control tasks in individual task settings, some other limitations of this study should be highlighted. First and most important, this conceptualization of task complexity is a first attempt in capturing this construct when talking about dynamic stock control tasks. It does not pretend to be exhaustive, nor does it pretend to be based on solid empirical evidence. Exhaustiveness might even be impossible for similar reasons as Hackman (1969: 110) pointed out that defining tasks in terms of 'objective' properties of tasks may never be exhaustive because of the almost limitless number of possible descriptive dimensions which are available. Second, this paper draws heavily on Liu & Li's (2012) paper called 'Task complexity: a review and conceptualization framework'. However, clear choices are made to differentiate our conceptualization of task complexity of dynamic stock control tasks for their 'generic' task complexity construct. Some of their complexity contributory factors and complexity dimensions were, to our opinion, still quite subjective in nature. These were if possible converted to objective factors or dimensions, or removed from our conceptualization. Liu & Li's (2012), for instance, also include 'action complexity' as a dimension in their task complexity contruct. Action complexity is specified as the cognitive and physical requirements inherent in human actions during the performance of a task. For example, the complexity of activating a button and of detecting an occurrence of an alarm would be different. To our oppinion, action complexity is subjective and is therefore removed from our conceptualization. Nevertheless studies illustrate the importance of this dimension for human-computer interaction (e.g., Bedny, Karwowski, & Bedny, 2012).

Lastly, we want to illustrate the value of our conceptualization of task complexity for future research on human understanding of dynamic stock control tasks. Apart from just the value it brings to the deeper understanding of the task complexity concept and providing a basis for the operationalization and hopefully measurement of the construct in the near future, we also see huge value for task design as well as for task rehearsal strategies. We will try to briefly illustrate these last two by returning back to Gonzalez & Dutt (2011) dynamic stock control task which we have discussed earlier (see figure 1). To quickly recap, the objective of the task is to increase two gallons of water in an accumulation to four and keep it at that level afterwards. The accumulation has two inflows and two outflows. One of each is within the task performers' direct control (i.e., decision variables) and one of each is an exogenously defined environmental inflow and outflow, respectively. The procedure in order to perform the task was organized in such a way that instructions were given to the task performers on the computer before engaging in the task. Participants were encouraged to ask questions after reading the instructions and were also handed a paper copy of the instructions. Participants were not given any information concerning the nature of the environmental inflow and outflow, and were told that these environmental flows were outside their control over the entire course of the task. They were asked to control the accumulation for 100 time periods which completed the task.

In designing such tasks in the future, our task complexity construct can now be used in order to make task designers more aware of their choices in task design and how that might affect task performance and/or learning outcomes. Each complexity dimension of our task complexity construct can be considered in task design. Gonzalez & Dutt (2011) have, for instance, presented the instructions required to perform the task in a very heterogeneous manner as they were presented both computer-based and paper-based. In addition, having the instructions on paper during the task might also affects the way in which task performers process information (e.g., simultaneous or sequential processing). Furthermore, the current state of water level and the goal are both visually represented on the user-interface in the form of a graph and in the form of a number which might include some redundancy. The task contains also ambiguity since the task does not provide clear information about rules that govern the environmental inflow and outflow. More comments like these could be formulated based on our conceptualization of task complexity. However, it needs to be pointed out that these comments do not necessary detract from the design of this task or compromise the results of the study. They just illustrate that our conceptualization of task complexity can make task designers more aware of the choices they make in designing tasks. Future research could also use our conceptualization of task complexity and turn it into a tool to assess the complexity level of tasks. Furthermore, our conceptualization could form the basis for a tool that provides a standard for describing and later on maybe measuring task complexity of dynamic stock control tasks in future research on human understanding of dynamic stock control tasks. Eventually, the insights gained from this line of inquiry might yield dynamic stock control tasks that are designed in a way that overcomes poor performance in managing dynamic complex systems.

Next to task design, our conceptualization of task complexity can also play a role in developing more engaging task rehearsing strategies with regard to dynamic stock control tasks. Rehearsal as a strategy to increase task performance over successive trials have been applied in many studies, often in combination with providing information feedback about the reaction of the system to decisions made in the task. Rehearsal in these studies was mainly just performing the same task multiple times in a row which has not yet been proven hugely successful in increasing task performance (e.g., Gary & Wood, 2011; Langley & Morecroft, 2004; Özgün & Barlas, 2012; Paich & Sterman, 1993). Wisely varying different complexity contributory factors over successive trials might be a strategy that could improve task performance through making rehearsal more challenging. There is, for instance, evidence that adding uncertainty (the variability-complexity dimension) to the task in the form of stochasticity to the simulation model can affect motivation which in turn might affect task performance (e.g., Ozcelik, Cagiltay, & Ozcelik, 2013). Another option lies, for instance, in the 'gradual increase in complexity' approach where the complexity of the task is increased gradually over the successive trails in order to increase task performance in relatively complex tasks (e.g., Yasarcan, 2010).

6. CONCLUSION

The objective of this paper was to undertake a first attempt at carving out what task complexity entails within the context of dynamic stock control tasks in order to determine its usefulness for future research on human understanding of such tasks. This paper illustrates that objective task complexity of a dynamic stock control task consists of ten dimensions: 1) size: in terms of the quantity of task components; 2) variety: defined as the heterogeneity in task components; 3) redundancy: capturing the needlessness of task components; 4) ambiguity: defined as the degree of clarity of certain task components; 5) variability: in terms of changes in or unstable characteristics of task components over time; 6) unreliability: specified as the inaccuracy of certain task components where accuracy is about reflecting the real world; 7) novelty: as referred to the appearance of novel, irregular and non-routine events/actions or presentation formats within the task; 8) incongruity: in terms of the inconsistency, mismatch, incompatibility of task components; 9) connectivity: as the interrelateness of the control system represented in the form of a simulation model; and 10) temporal demand: specified as time pressure or concurrency between tasks and/or presentations imbedded in the task.

This 'new' and detailed conceptualization of task complexity is valuable for future research on human understanding of dynamic stock control tasks. Future research on task complexity can now focus on how the identified complexity dimensions or complexity contributory factors affect human understanding of tasks. Investigating task complexity in more detail might lead to better task design or better strategies to use tasks more effectively resulting in improve human understanding of such task. All this is of great importance, as task complexity has been found to be an important factor that influences and predicts human performance and behavior (Liu & Li, 2012).

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