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Human–Automation Interaction Strategies and Models for Life Science Applications

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ABSTRACT

The objective of this research was to identify current and future approaches to the design of automated systems for life science processes, including humans in control loops, in applications such as high-throughput compound screening and high-performance analytical chemistry. The identified approaches were classified according to existing theories of human-centered automation, which provided a basis for projecting human performance implications. We provide background on the life sciences domain and established theories of types and levels of automation (LOAs) in complex human–machine systems. We describe specific forms of robotic and automated technologies used in life science applications and the general design of high-throughput screening (HTS) and analytical systems to accommodate particular process configurations. Example classifications of life science automation (LSA) schemes are presented by referring to a taxonomy of LOAs from the literature. We project the implications of these classified forms of automation on human performance on the basis of prior empirical research in other domains. A mathematical model for predicting the cost of LSA from an operator perspective is also defined to support hypotheses for future study. Finally, we identify the need for additional empirical research on human performance consequences of LSA and remedial measures, including enhanced supervisory control interface design. © 2009 Wiley Periodicals, Inc.

1. INTRODUCTION

In the last two decades, there have been major advances in laboratory automation for life science processes (cf., Thurow & Stoll, 2001). These advances have been motivated, in part, by demands for high-performance analytical chemistry and high-throughput biological screening in drug development processes. The potential for safety risks for laboratory workers in handling chemical and/or biological compounds also has been a factor. Advanced automation, including optimized robots for chemical analysis (ORCAs) and automated analytical and measurement systems, has been employed in the life science domain to address these needs through single and complex, multiple process applications.

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1.1. Overview of High-Throughput Screening Applications

High-throughput screening (HTS) of biological compounds involves a series of common tasks for the majority of tests (assays), including: 1) preparing samples, 2) assembling the assay, and 3) detecting "signals" or active compound under test conditions. Each of these operations requires an integrated system of automated devices that is typically structured in a multiple process line. Example equipment includes robots for moving samples, barcode scanners for tracking samples, liquid-handling devices for facilitating chemical assays, signal-detection devices for determining if a compound is useful, and incubation (heating) and storage devices to ensure that tests are conducted under proper conditions. (We present figures of many of these devices and integrated configurations in this article.) Samples, reagents, sample storage containers, and other consumables are supplied to the integrated system for processing.

Robots typically transport microculture plates to and from analytical devices on a process line. Commercial incubators and storage devices are typically designed to be compatible with robot manipulators. Liquid handling, or automated pipetting devices, may be used to fill microplates with enzyme substrates, test compound extracts, and other reagents for screening processes. These devices also integrate a variety of tools, such as different pipettors and grippers, to perform tasks, such as serial dilutions, washing or aspirating of pipettors, and liquid transfers between microculture plates. Process signal-detection devices are used for analytical measurements on compound samples (e.g., luminance and fluorescence tests) based on the target chemical reaction products identified by expert biochemists before the screening process. All automated devices are typically controlled in an assay protocol by an operator using a process control system (PCS).

1.2. Current Issues

Although the development of such automated technologies has been considered important to accelerating the discovery of useful compounds for new drug therapies (cancer and virus medications, etc.), it also has led to dramatic changes in the role of human operators in laboratory environments. Laboratory workers, who were once involved in manual sample preparation and assay handling, have been replaced with automation and robots programmed to mimic model worker task performance. Operators that at one time worked with individual automated tools are now working as assay method developers transforming benchtop procedures for implementation on parallel, automated workstations (cf., Entzian et al., 2005). They are involved in programming, monitoring, and managing high-throughput processes as well as data analysis using laboratory information management systems (LIMS; Thurow, Göde, Dingerdissen, & Stoll, 2004).

The potential implications of this change on human performance recently have been studied in other work (Kaber, Segall, Green, Entzian, & Junginger, 2006). In general, laboratory automation has removed operators from direct process control, but it also has imposed high monitoring workload. The nature of automated operations has caused a change in the quality of operator workload from manual (physical) labor to more cognitive labor. This change occurs under time pressure, as laboratories typically have demanding test volume targets. There is a standing need to identify effective strategies for integrating life science automation (LSA) and humans by considering functional capabilities of systems, performance objectives, the potential implications of the automation on the operator, and cost.

1.3. Objectives

This research reviewed relevant theories of human-centered automation (HCA) and identified current and future strategies in LSA for specific human-in-the-loop applications. These strategies were then classified in terms of levels of automation (LOAs), described in the existing theories. This classification allowed for projection of human performance implications of specific approaches to LSA, based on prior empirical research results. Recommendation was made as to how automation-induced problems in the life sciences domain could be addressed through new design strategies. Beyond this, a theoretical model for predicting the cost of LSA from an operator perspective was defined to support hypotheses for future study. Finally, future empirical research and complex system interface design needs were identified to address projected human–automation interaction pitfalls.

2. REVIEW OF HCA THEORIES

Several theories of HCA previously have been presented in the human factors literature (Endsley, 1987; Kaber & Endsley, 1997; Parasuraman, Sheridan, & Wickens, 2000; Sheridan & Verplank, 1978). These theories have focused on identifying generic information-processing functions that can be performed by humans or machines and presenting function allocation schemes feasible in the context of complex systems (e.g., telerobots, automobiles, automated aircraft, air traffic control). Theoretical LOAs are defined in terms of the distribution of functions to a human or machine for performance.

2.1. Types of Automation

Sanders and McCormick (1993) identified complex system information-processing functions that could be automated, including sensory processing (detection), perception and information storage (use of working or temporary memory stores), decision making (based on information analysis capabilities), and response selection. Parasuraman et al. (2000) also identified similar general automated system functions in their theory of types and LOAs, including information acquisition and analysis, decision selection, and action implementation. They said that each of these functions could be automated to varying degrees in the human–machine system design and development process. Kaber and Endsley (1997) also identified a general set of information-processing functions automated across existing complex systems, including monitoring, generating processing plans, and selecting and implementing options. They also considered the degree to which each of these functions is automated to be variable and that humans and computers might share functions.

2.2. LOAs

By specifying which entity (human or computer) is responsible for each system function, Sheridan and Verplank (1978) described ten LOAs for underwater telerobot control, ranging from manual control (Level 1) to full automation (Level 10), including intermediate levels blending human and computer control. For example, the mid-level in Sheridan and Verplank's taxonomy involves the computer suggesting to a human a decision alternative and the computer executing the suggestion if the human approves. Higher intermediate LOAs involve human veto of computer decisions or automated system operation with feedback to the human upon request. This taxonomy of automation is focused on how the decision

TABLE 1. Kaber and Endsley's (1997) Taxonomy of LOAs

	Information Processing Functions			
Level of Automation	Monitor	Generate	Select	Implement
1. Manual control	H	H	H	H
2. Action support	H/C	H	H	H/C
3. Batch processing	H/C	H	H	C
4. Shared control	H/C	H/C	H	H/C
5. Decision support	H/C	H/C	H	C
6. Blended decision making	H/C	H/C	H/C	C
7. Rigid system	H/C	C	H	C
8. Automated decision making	H/C	H/C	C	C
9. Supervisory control	H/C	C	C	C
10. Full automation	C	C	C	C

Note. H: human; C: computer.

selection function is allocated to a human or computer in automation design and the allocation of functions to an agent was exclusive.

Endsley (1987) also presented a taxonomy of LOAs developed in the context of human use of expert systems for automated systems control. She identified five functions that either the human operator or expert system could perform including "suggest," "concur," "veto," decide," and "act." Endsley presented five LOAs by structuring allocation of these roles to both servers ranging from "Manually" (human decides and acts with no assistance from the system) to "Full Automation" (expert system decides and acts with no operator interaction). Intermediary levels included "Decision Support" (human decides and acts under suggestions by the expert system), "Consensual AI" (expert system decides and acts with the concurrence of the operator), and "Monitored AI" (expert system decides and acts unless the human exercises veto authority).

Kaber and Endsley (1997) developed a ten-level taxonomy of automation similar to that of Sheridan and Verplank (1978), ranging from manual control to full automation (see Table 1). They sought to define intermediate modes of automation incorporating a planning function and to identify modes for supporting operator situation awareness (SA) and reducing workload. These modes included "batch processing" in which the human and computer jointly monitor the system, the human generates processing plans and decides which plan to use, and the computer implements the plan. This LOA is representative of forms of automation historically applied to life science processes. (We say more about this later.) Another higher intermediate LOA was "blended decision making," which involves joint human and computer monitoring of system states, generation of decision options, and selection followed by computer implementation. By making explicit how system monitoring, process planning, decision making, and response execution all can be assigned to an operator or computer or shared between the two, this taxonomy provides a high level of detail on "who" is doing "what" at each LOA.

More recently, Parasuraman et al. (2000) presented a similar LOA taxonomy that considered whether each of four general system functions identified earlier in this article were automated. The information acquisition, decision selection, and action implementation

functions of this model are comparable to the monitoring, selection, and implementation functions of Kaber and Endsley's (1997) taxonomy. However, this model does not explicitly consider the option generation (planning) function. Instead, it provides information analysis as a separate function to be automated. Parasuraman et al. (2000) did not explicitly identify LOAs, involving different distributions of functions to human and machine, but discussed how the degree of automation for each function could range from "low" to "high" along different continuums, depending on the function.

2.3. LOAs and Human Performance

Unfortunately, specifying the best LOA for a particular system and application does not turn out to be as straightforward as one might think. Parasuraman et al. (2000) identified several criteria for selecting among LOAs in complex systems design, including human performance, automation reliability, and cost associated with outcomes. Specific human performance criteria include the potential for operator complacency, vigilance decrements, loss of SA, and skill decay over time. To effectively use such criteria for LOA decisions, data on system performance are necessary or an elaborate iterative design process must be undertaken.

To provide a general basis for automation design decisions, some empirical studies have been conducted on human performance across multiple LOAs included in the taxonomies described earlier in text. Endsley and Kiris (1995) assessed the affect of the five LOAs formulated by Endsley (1987) on performance in use of a decision support tool for vehicle route navigation. They found that SA was lowest under full automation and only slightly lower under intermediate LOAs, as compared to completely manual task performance. They also demonstrated that lower SA correlated with performance decrements when the automation failed and operators were forced to perform the task manually.

Performance, workload, and SA implications of LOAs in Kaber and Endsley's (1997) taxonomy have been assessed through several studies using different types of tasks [Endsley & Kaber (1999)–radar monitoring; Kaber, Onal, & Endsley (2000)–telerobot control; Kaber & Endsley (2004)–air traffic control–related tasks]. Endsley and Kaber (1999) demonstrated that the batch-processing mode of automation (see Table 1) supported operator achievement of SA, as compared to manual control and full automation, under normal operating conditions; however, operator advanced planning for system performance and machine implementation led to increased error recovery times. Kaber, Onal, and Endsley (2000) demonstrated that the intermediate "decision support" mode of automation (also see Table 1), involving joint human and computer monitoring and generation of system-processing options, human decision making, and computer implementation of options, applied to telerobot control tasks served to increase SA and reduce workload. Similarly, other work (Kaber & Riley, 1999) has shown that periodic allocation of the blended decision-making mode of automation during manual control allowed for effective operator workload management within a predefined, desired range. In general, these studies have revealed that intermediate LOAs in complex systems control may have some benefit for SA and workload.

Parasuraman et al. (2000) also speculated about the implications of various LOAs in their taxonomy on human performance in the context of air traffic control tasks. They said that high-level information acquisition and analysis automation was possible with reliable computing technology and that high-level decision automation also could be used in low-risk situations. High-risk tasks were considered to limit the use of decision automation.

They also recommended that when high-level decision automation is used, low-level action implementation automation is necessary to maintain operator involvement in the system control loops and for system state awareness. Adaptive automation of these functions and human information processing also has been investigated in an air traffic control–related tasks (Kaber et al., 2005). This research demonstrated that humans can more effectively adapt to and use automation applied to action implementation versus information analysis and decision automation.

In general, the taxonomies of automation presented in the literature can be useful for classifying real-world systems in various domains. Empirical research on human–automation interaction has demonstrated that both types and LOAs appear to play a critical role in cognitive processing and workload. The results of the studies mentioned can be generalized to different types of systems involving similar forms of human and machine information-processing functions or as a basis for predicting human performance consequences of new forms of automation in systems.

3. TYPES AND LEVELS OF LSA

The automation systems used in life science processes can generally be grouped as: (1) laboratory robot-based systems for chemical, biological, and analytical applications; (2) liquid handling or pipetting systems; and (3) (catalytic) reaction technologies used to accelerate chemical reaction processes in substances. The PCS used to integrate these technologies also transmits device data to a LIMS for processing. The robots and pipetting machines represent "actuators" in this domain, and the PCS and LIMS represent "information technologies." The robots primarily facilitate material flow whereas the PCS and LIMS are critical to information flow. Automation of each of these flows may range from manual control to full automation with low, intermediate, and high levels blending human and machine (look ahead to Figure 4).

There are three general process scenarios to which automation can be applied in the life sciences domain, including: (1) a single process involving planning and control, an assay or chemical test, and data analysis; (2) multiple, simultaneous processes, all involving planning, testing, and data analysis stages; and (3) complex processes in which multiple planning, testing, and data analysis operations are completed simultaneously with interconnections among the processes creating dependencies. The second class of multiple simultaneous processes can be broken down further into: (a) processes that involve the use of equivalent systems/robots to perform operations of equivalent length under the control of equivalent software; and (b) processes using equivalent systems with different operation lengths or workflows. It is also possible to further decompose these processes into sets involving processing of the same material samples, but through the use of different systems. That is, the "means" are different for accomplishing the processes, but the "ends" are comparable. In systems involving multiple simultaneous automated processes, multiple PCSs are integrated with a single LIMS for exchange of process data and planning information. Related to this, by definition, the complex process class (mentioned earlier in text) involves the use of different systems with different workflows.

3.1. Automation for a Single Life Science Process

The historical developments in LSA began with laboratory automation in analytical chemistry (i.e., integrated autosampling systems for chromatography and spectroscopy) and

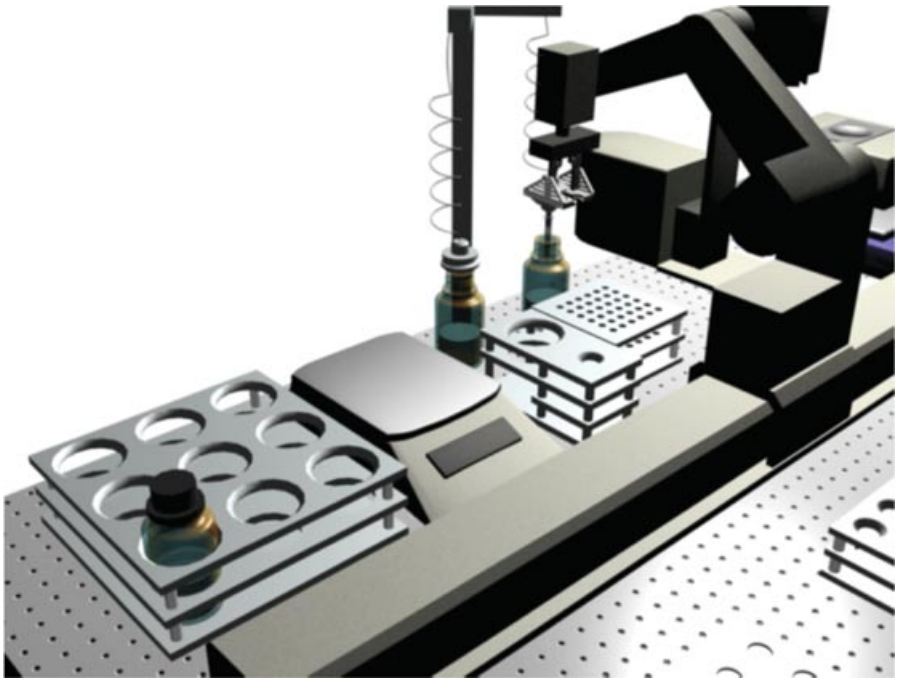

Figure 1 Model of an ORCA programmed for liquid dispensing.

gained significant momentum in the late 1980s and early 1990s with the development of enhanced laboratory robots. The first robotic approaches focused on classical industrial robots used in manufacturing processes. For example, Cartesian coordinate (*xyz*) robots were used for liquid sample handling and delivery. Chemists saw the robot as a kind of "universal" machine performing all functions needed in the automation of laboratory processes. Initially, the processes to which robots were applied also came from the field of analytical and environmental or combinatorial chemistry. The robots used in these processes had a high number of degrees of freedom to promote flexibility and to allow for many functions. Various companies, such as Hewlett Packard, developed ORCAs for liquid dispensing, sample containment procedures, and so forth (see Figure 1). In this stage of automation development, the human operator's role was focused on robot position programming, providing materials to the robot, and directly monitoring sample preparation processes. The operator would then move samples to other devices and manually coordinate an assay.

The application of automation in life sciences subsequently expanded to address problems in molecular biology. In general, laboratory automation systems became more complex. Implementations moved from centralized robot systems to distributed robots integrated with islands of automated analytical and measurement devices. For example, a single-vial handling robot (e.g., a CTC or Zymark system) might be integrated with a separate robot for sample containment (lid replacement), another device for sample weighing, and a sample shaker. The ORCA would be used for microculture plate transport among the various devices. This type of development followed a philosophy of creating automated laboratory workbenches. Distribution of the robotic systems allowed for more narrow specification of robot functions and the use of lower degree of freedom actuators in subsystems. For

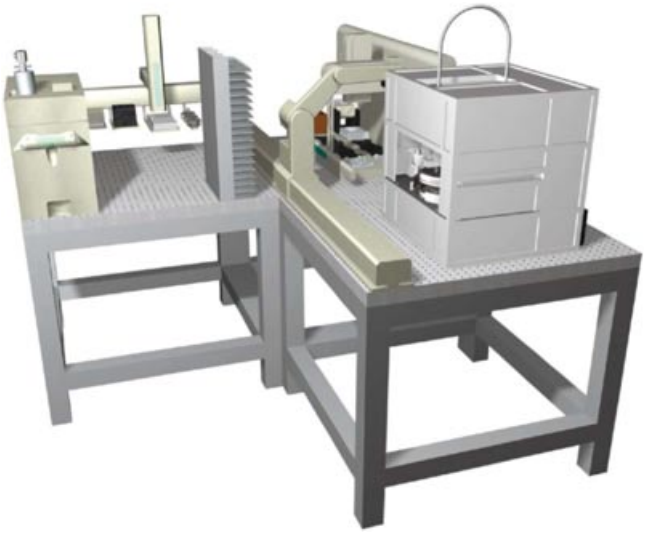

Figure 2 A distributed robot system and laboratory workstations.

example, some robots were used strictly for material transport. The distributed approach to automating laboratory processes was, however, more flexible and easier to adapt to new life science needs.

In contemporary applications of distributed robotics in life science processes, a master robot is integrated with multiple automated analytical and measurement systems allowing for parallel operations and processing of multiple samples simultaneously (see Figure 2). A typical single life science process begins with the delivery of the microplates, chemicals, plate labels, and pipetting consumables to the process line by a human operator. These samples, reagents, plates, and consumables are then distributed to liquid-handling instruments, plate readers, and automated plate handling and storage devices by a material transport robot. The next step in the process is a operator planning and program of the automated screening test protocol using a computer-based "method editor." The specific tasks to be performed by devices and the sequence of the automated devices is programmed, including defining pipetting processes. During the analytical process, the automated devices follow the screening test protocol established by the human operator. The operator performs monitoring of the steps in the automated assay. At the conclusion of the automated process, data files are produced for use in compound screening data analyses. Finally, the operator generates and implements the data analyses using computer-based programs to create reports of the results of the assay for delivery to clients. A flow diagram depicting these steps with the points at which human, computer, or both agents share the task can be seen in Figure 3.

3.2. Automation for Multiple Life Science Processes

The automated laboratory workbench philosophy required a change in software tools for life science processes. In general, software development moved from a sequential coordinate-oriented programming philosophy (for single, fixed-location robots) to a scheduled, object-oriented mode of operation (for distributed robot systems), in which automated subsystems were defined as three-dimensional workspaces on an automated workbench. Each workspace

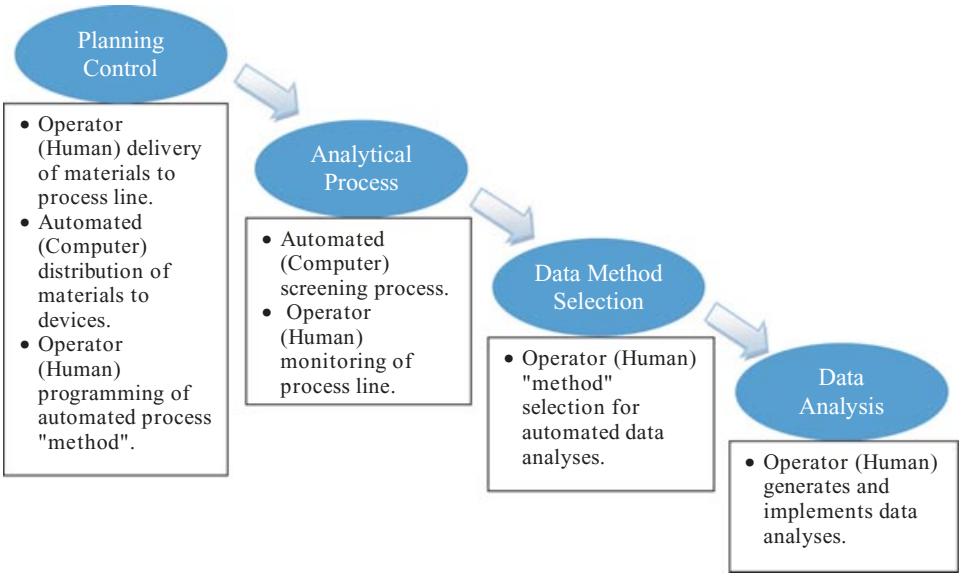

Figure 3 Example single life science process workflow with human and computer roles.

element and, consequently, automated bench had defined material- and information-related input and output functions. This allowed for the development of scheduling systems for LSA, starting with static schedulers and developing into dynamic scheduling modes of operation for contemporary applications. Such tools paved the way for multiple process automation.

As outlined earlier in text, one can consider laboratory automation applications for multiple processes requiring equivalent or different systems to execute equivalent or different workflows. The simplest scenario is graphically portrayed in Figure 4, wherein three processes of equal length, requiring similar automation, are performed simultaneously. Although the devices are the same, the LOA may vary depending on the human and machine function allocation. An example of this might be a single operator monitoring three gas chromatograph systems executing the same processes on similar samples and performing data analyses.

A more complex, multiple process automation scenario would involve different equipment and different methods. A good example system is the use of modular liquid-handling robots (e.g., a CTC HTS device, combining sample preparation and autosampling) for analytical (compound) screening assays. Such devices allow for sample filtration, dilution, agitation, injection, heating, and container washing. A multiple process automation scenario could involve three CTC systems integrated with three different analytical devices, such as a gas chromatograph, a mass selective detector, or atomic emission detector to perform different, required methods. Figure 5 graphically portrays this process scenario. The only constant across processes is the material samples being handled. Otherwise, the systems, LOA, and process workflows, as well as schedules, may all be different. Beyond this, the planning of one process may depend on any other because of the availability of materials, devices, or time.

At this LOA development, a single operator may be tasked with planning the control of all three processes, monitoring the execution of the processes through a LIMS, and

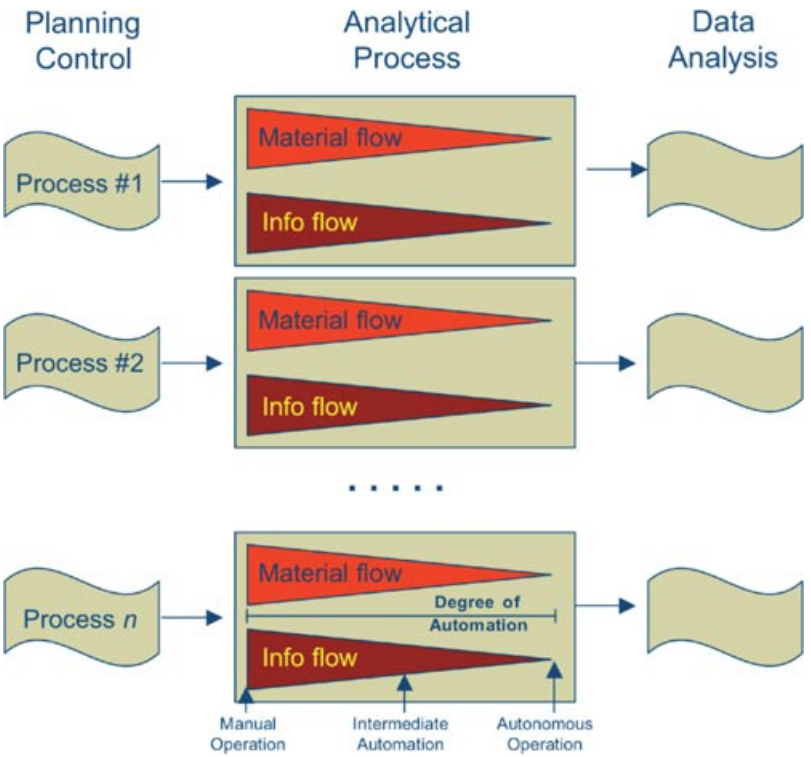

Figure 4 Multiple process automation with equivalent systems and workflows.

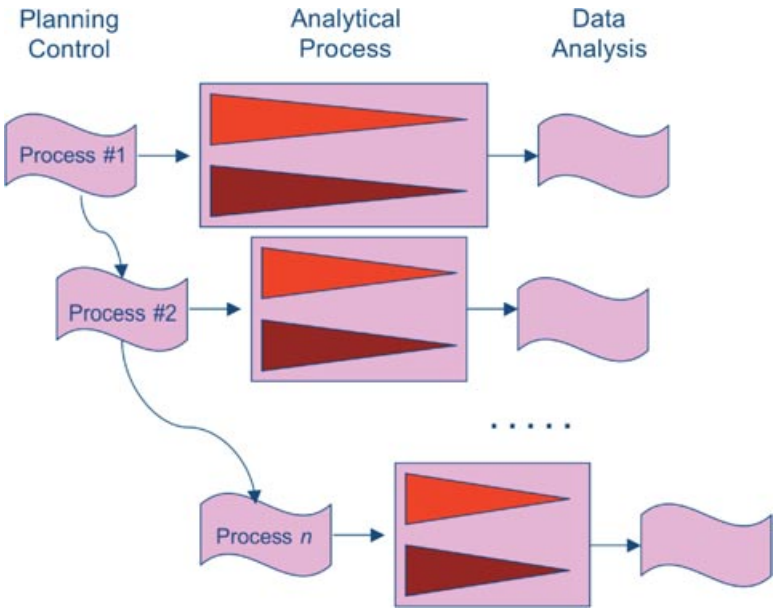

Figure 5 Multiple process automation with different systems and workflows.

performing data analyses. Because the process operations may be staggered, developing an internal schedule to address these functions adds to the operator's workload. Furthermore, the data analyses for each process would need to occur in a sequential manner to identify any abnormal results that would need to be investigated. As the number of lines increases, so would the workload in terms of the data analysis required by the operator.

3.3. Automation for Complex Life Science Processes

As described, early laboratory automation strategies were defined for robot handling of single samples in sequential operations. The needs of new life science processes, especially for HTS in the field of molecular biology, motivated the development of automated systems for parallel processing of samples using microculture plates with 96, 384, or 1,536 wells. In general, such HTS applications involve small sample volumes but large sample sizes. This development was also motivated by cost criteria. Small volume operation in LSA and highly parallel liquid-handling systems and plate readers allowed for process costs to be dramatically reduced.

In complex automated setups for HTS processes, a single LIMS may be integrated with multiple PCSs that are used to control different processing lines for development of reagents (or reaction technologies), preparation of reactions, test sample preparation, and analysis. All of these processes may be dependent on each other and involve the use of different systems and different operation lengths. Furthermore, it is possible that there may be multiple instances of each type of process occurring in parallel or in a temporally staggered manner. Separate planning and data analysis operations may be part of each instance of a process (see Figure 6).

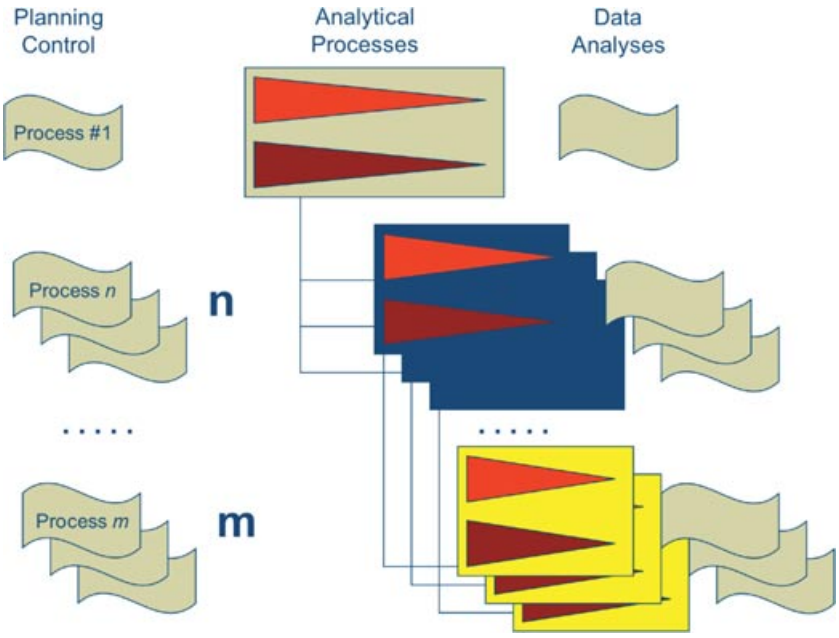

Figure 6 Complex process automation involving different systems, different processing lengths, and dependence among operations.

Figure 7 Multiple process operator using LIMS workstation.

This situation can lead to a high workload for operators, who need to maintain awareness of target chemical reactions, monitor ongoing performance of automated devices, communicate with other operators (who may be at remote locations), determine whether the data being generated by various processes are acceptable, and so forth (see Figure 7 for a photo of an example operator workstation). It is not uncommon in current laboratory environments for operators to supervise multiple automated workbenches or compound screening lines simultaneously and to use multiple software applications, as part of a real-time LIMS, and displays. Another general drawback associated with such complex process automation and operator tasking is that, as the number of devices increases, the probability for processing errors also increases. Consequently, human capabilities for detection and diagnosis of faults as well as remediation become more critical. With integrated HTS lines, human planning and supervision of devices is critical to effective process execution. In these scenarios, the planning component of the process requires more attention to maintain individual HTS line efficiency.

4. THEORETICAL CLASSIFICATION OF APPROACHES TO LSA AND MODELING OF HUMAN PERFORMANCE IMPLICATIONS

In this section, we categorize those types of LSAs reviewed according to taxonomies of LOAs. Following this, we provide novel qualitative and quantitative models for prescribing effective LOAs for life science applications. The vast majority of LSA systems in use today can be classified as supervisory control systems. By definition, supervisory control involves human programming of an automated system and continual monitoring of information

from a computer that closes an autonomous control loop in the system (Sheridan, 1992). In any of the taxonomies of automation reviewed earlier in text, this represents a high LOA, just shy of fully autonomous operation. For example, Kaber and Endsley (1997) identify supervisory control as Level 9 in their 10-level taxonomy (see Table 1). Under normal operating conditions, the computer performs all functions while the human monitors. Unfortunately, a number of studies have observed this role to be one to which humans are ill-suited and one that can lead to performance problems, including complacency, vigilance decrements, and loss of SA (e.g., Parasuraman, 1987; Wiener, 1988). Under system failure modes, operators are expected to detect and diagnosis errors, to intervene in the control loop, and to recover and return the system to automation. According to Kaber and Endsley (1997), the system reverts to a decision support mode of automation (Table 1, Level 5) in which the operator and computer jointly monitor system states and generate processing plans; however, the human has the final decision-making authority regarding remedial measures, and the computer implements the selected plan. Unfortunately, the problems in human monitoring under high-level automation may lead to slow error detection and recovery. Empirical research has demonstrated that, when breakdowns occur in supervisory control systems, human performance is better when lower LOAs for information acquisition and control are adopted before critical conditions develop (Sharit, 1984).

Based on the descriptions of the operator roles with complex and multiple life science process automation, these forms of automation can be classified as supervisory control. However, operator functions with single process automation are indicative of a batch-processing mode of control (Table 1, Level 3) in which the human is responsible for all information-processing functions, save action implementation. Under normal operating conditions, Kaber et al. (2000) found that supervisory control and full automation produced a performance advantage over batch-processing automation as a result of computer control of robot motion in a material handling and inspection task (see Figure 8). Batch-processing modes of automation may be less desirable for LSA applications because operators are required to routinely generate material-processing plans and they may adopt "wait and see" strategies to ensure the success or safety of a plan versus exploiting any advance planning control capability of a system.

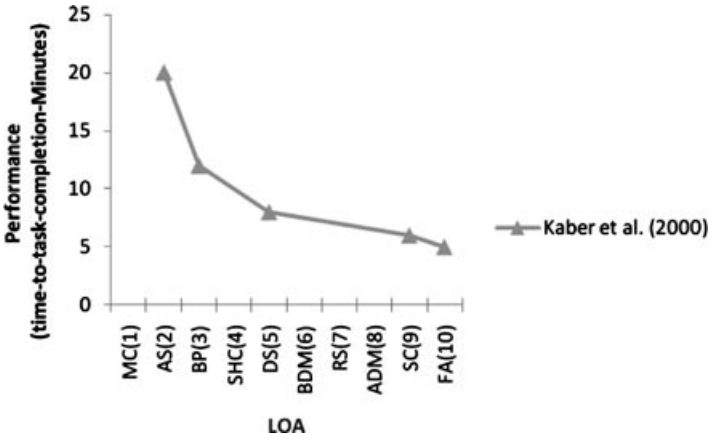

Figure 8 LOA vs. job performance (time-to-complete the task).

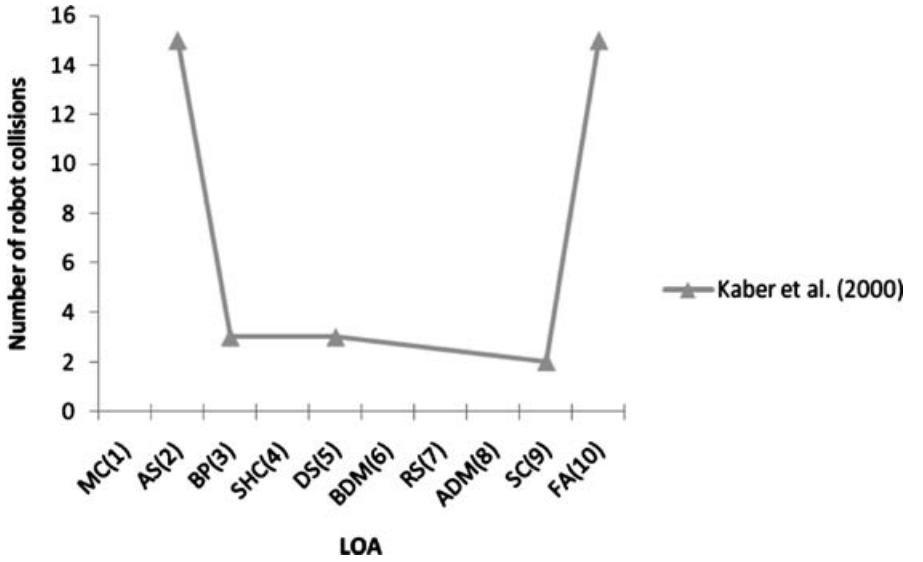

Figure 9 LOA vs. number of robot collisions.

Opposite to this finding, Kaber et al. (2000) found that intermediate LOAs, including batch processing, significantly reduced the occurrence of errors in robot material-handling control, such as collisions with other objects in the work environment or damage to materials, as compared to manual control and full automation (see Figure 9). Intermediate LOAs like batch processing allow for human generation of safe control plans and selection of optimal plans, whereas the complexity of manual control may lead to high workload for operators and errors may simply go undetected or unchecked under high LOAs, including supervisory control and full automation. It is also important to note here that when artificial system errors were introduced into robot material-handling operations, Kaber et al. (2000) found that operators were slower to recover the system if the failure had been preceded by a high LOA versus an intermediate LOA.

In general, these empirical results regarding LOAs for robot control in material-handling operations suggest that a blend of intermediate automation, such as a batch-processing mode, with higher level automation, like supervisory control, throughout life science processes may be used for promoting operator control involvement in preparation for error handling and, at the same time, serve to reduce operator cognitive workload during periods of high demand. Use of these modes of automation to maintain operator involvement in screening or analytical process outcomes and to prevent overload conditions also may lead to increased operator job satisfaction.

4.1. A Qualitative Modeling Approach

One approach that may be used to define an optimal mode of LSA is to identify the critical operator functions in each type of life science process and the possible LOAs that would serve to promote operator performance. Table 2 presents a prioritization of operator information-processing functions for single, multiple, and complex life science processes. For single life science processes, generating (G) and planning the methods for use of analytical devices is

TABLE 2. Rank of Critical Information Processing Functions for Each Type of LSA Process

	Priority Ranking of Critical Functions			
LSA Process Type	1	2	3	4
1. Single	G	M	S	G/I
2. Multiple	S	G/I	M	G
3. Complex	G	S	M	G/I

Note. M: monitoring; G: generating; S: selecting; I: implementing.

most important, followed by monitoring (M) analytical processes, selecting (S) programmed methods during analytical processes, and generating and implementing (G/I) data analyses. (Some of the process tasks were found to involve multiple types of functions performed together.) For multiple life science processes, the function of selecting programmed methods during analytical processes is most important, followed by generating and implementing data analyses (in sequence, for multiline setups and error resolution), monitoring analytical processes, and generating and planning methods for analytical processes (in that sequence). The critical function sequence for complex life science processes included generating and planning methods for analytical processes, selecting programmed methods during analytical processes, monitoring analytical processes, and generating and implementing data analyses (including proper follow-up on errors). As can be noted from this analysis, operator planning (generating) and decision making (selecting) are key to all process types.

Based on previous research (Endsley & Kaber, 1999; Kaber et al., 2000; Kaber & Endsley, 2004), we identified the "best" and "worst" LOA conditions for supporting the information-processing functions of monitoring, generating, selecting, and implementing in complex systems from a task performance, workload, and SA perspective across different types of tasks. This analysis showed that, for task performance, intermediate-level monitoring automation should be combined with high-level planning, selection, and implementation automation (see Table 3). This combination actually represents a supervisory control LOA, whereas, for reducing workload and improving operator comprehension on system states,

TABLE 3. Optimal Function Allocations Based on Various Response Measures

Human Performance Criteria	Allocation of IP Functions			
	Monitoring	Generating	Selecting	Implementing
1. Task performance	Intermediate (H/C)	High (C)	High (C)	High (C)
2. Workload	Intermediate (H/C)	Intermediate (H/C)	Intermediate/ High (H/C or C)	High (C)
3. System state comprehension	Intermediate (H/C)	Intermediate (H/C)	Intermediate/ High (H/C or C)	High (C)
4. System state projection	Intermediate (H/C)	High (C)	Intermediate (H/C)	Intermediate (H/C)

Note. H: human; C: computer.

intermediate-level monitoring and generating/planning automation should be combined with intermediate- to high-level selection automation and high-level implementation automation. These combinations are closest to Blended Decision Making (LOA 6) and Automated Decision Making (LOA 8) in Kaber and Endsley's (1997) taxonomy of automation. Similar results were obtained for operator system state projection. In general, intermediate-level monitoring and implementation automation should be combined with high-level generating and low-level selection automation to improve system state projections. However, there is no LOA explicitly defined in Kaber and Endsley's taxonomy that exactly matches this combination.

These analyses lead to the following LOA recommendations for single, multiple, and complex life science processes. In the single process scenario, to support task performance, the generating function should be allocated to computer control (as in Kaber and Endsley's LOA 7 or 9). The monitoring and selection functions should be shared between human and computer to reduce operator workload and promote process comprehension (as in LOA 6). Finally, to support all aspects of human performance, the implementation function also should be allocated to computer control (as in LOAs 5 through 9). In summary, it can be interpreted that the LOA required for single process LSA may be between LOA 6 and 7 in Kaber and Endsley's taxonomy.

With respect to multiple process scenarios, the recommend function allocations are as follows. To reduce operator workload and promote process comprehension, the selection function should be either shared between human and computer or allocated to computer control (as in Kaber and Endsley's LOAs 6, 8, and 9). As with the single process automation, to support all aspects of human performance, the implementation function also should be allocated to computer control (as in LOAs 5 through 9). However, the monitoring and generating functions both should be shared between human and computer to reduce operator workload and promote system status comprehension (as in LOAs 4, 5, 6, and 8). In summary, it can be interpreted that LOA 6 (Blended Decision Making) may be a superior LOA for controlling multiple life science processes.

Finally, concerning complex life science processes, the generating and monitoring functions should be shared between human and computer to limit operator load and maintain process comprehension (as in Kaber and Endsley's LOAs 4, 5, 6, and 8). Similar to multiple process automation, the selection function should be shared between human and computer or allocated to computer control (as in Kaber and Endsley's LOAs 6, 8, and 9) to manage operator load and promote SA. Lastly, the implementation function should be under computer control (as in LOAs 3, 5, and 9) to support all aspects of operator performance. In summary, for complex life science systems, LOA 8 (Automated Decision Making) may be superior from an operator perspective.

4.2. A Quantitative Modeling Approach

Although using taxonomies of LOAs and making theoretical classifications of real-world system configurations may be a viable approach toward optimizing process automation, it may lack the quantitative rigor necessary for some system design processes. In general, there is a need for structured automation analysis tools to support designers in deciding on the degree of automation to introduce into a system (Haight, 2007). With this in mind, we also formulated a modeling approach that produces quantifiable results for specific forms of automation and allows for objective comparisons to be made. This type of modeling approach may be useful in the LSA domain and essential to expansion of the

concept of LOAs, in general, from simple to complex systems, involving multiple process control.

Based on the previous theoretical research and empirical studies (Kaber et al., 2000; Parasuraman et al., 2000), we developed a general automation cost function integrating variables for assessing LOAs in terms of human performance consequences, including perceived mental workload, SA, complacency and skill degradation, as well as outcomes and errors. The equation for a simple system may be formulated as follows:

$$Min \quad Y = X_1(MWL_{(i)}) - X_2(SA_{(i)}) + X_3(C_{(i)}) + X_4(SD_{(i)}) - X_4(P_{(i)}) + X_5(E_{(i)}),$$

s.t.

$MWL_{(i)}$ < Mental workload (overload) threshold for an operator,
$SA_{(i)}$ > Minimum functional level of SA for an operator,
$C_{(i)}$ < Complacency threshold for an operator,
$SD_{(i)}$ < Skill degradation threshold for an operator,
$P(i)$ > Minimum acceptable level of performance for an operator, and
$E(i)$ < Maximum acceptable number of errors for an operator.

Where

Y is the overall automation cost,
$MWL_{(i)}$ is perceived mental workload at the ith LOA of the target system.
$SA_{(i)}$ is operator situation awareness,
$C_{(i)}$ is the level of operator complacency,
$SD_{(i)}$ is the level of skill degradation,
$P_{(i)}$ is the level of operator output (e.g., number of tasks completed),
$E_{(i)}$ is number of errors committed by an operator, and
X_1, X_2, X_3, $X_{4,}$ $X_{5,}$ and X_6 are weights for the *MWL, SA, C, SD, P*, and *E* variables.

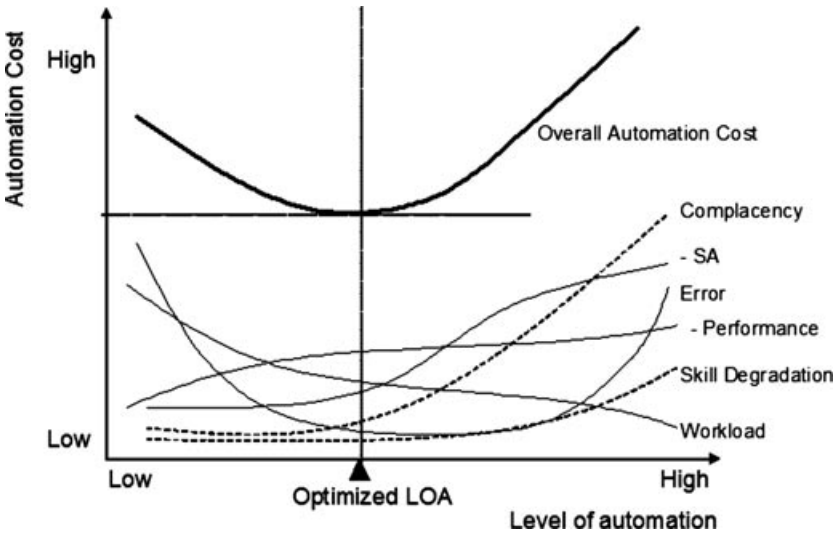

Figure 10 Profile of overall automation cost for deciding on an optimal LOA.

The formulated function can be evaluated for design utility by applying it to data from previous empirical studies. Figure 10 shows trends for various human performance measures across levels of system autonomy from low to high. The trends for mental work load, SA, performance, and number of errors (solid lines) were taken from Kaber et al. (2000) results. The trends for complacency and skill degradation (dotted lines) were inferred from Parasuraman et al. (2000) observations. The overall automation cost is plotted in the upper portion of the figure and integrates the trends on all variables presented in the lower portion of the figure. It should be noted that operator SA and performance have a negative effect on the automation cost function (see formulation that appears earlier in text), and hence the responses were drawn in a reverse manner in the figure (e.g., high SA under high automation). That is, higher SA and performance are desirable in system operation, whereas all other variables should be minimized.

In the figure, the overall automation cost has a U shape and a minimum point. This demonstrates that an optimal intermediate LOA can be identified for system design from an operator perspective. Of course the exact minimum point is dependent on the type of system being analyzed and the weights assigned to the various human performance variables in the cost function. Even though the graph and overall cost were roughly drawn in this analysis without specific weights for variables, the mathematical approach for finding an appropriate LOA produces outcomes in line with the results of the Kaber et al. (2000) study (asserting that low and intermediate LOAs may not only be useful, but preferable).

As life science applications may be complex, including different processes and systems, the new automation model may require additional dimensions. Consequently, the model can be expanded for complex systems as follows:

$$Min \quad Y = \sum_{j=1}^{n} \sum_{k=1}^{m} [X_1(MWL_{(i)(j)(k)}) - X_2(SA_{(i)(j)(k)}) + X_3(C_{(i)(j)(k)}) + X_4(SD_{(i)(j)(k)}) - X_4(P_{(i)(j)(k)}) + X_5(E_{(i)(j)(k)})]$$

s.t. same constraints as described for the simple model,
where i is the LOA (1 to 10),

j is the number of processes ($j = 1, 2, \ldots n$), and
k is the number of systems ($k = 1, 2, \ldots m$).

In general, it may be challenging for designers to define each coefficient and weight for the human performance variables in this model for application to complex systems. We propose that the coefficients and weights be identified through a series of empirical studies (e.g., regression modeling). In addition, any fully specified model should be validated with real system performance data to ensure a reliable basis for automation decision making in simple and complex systems with multiple processes.

Once a quantitative model is specified, it can be used to determine the optimal LOA and associated function allocations between human and/or computer for target systems by predicting automation costs based on human performance data. In this regard, it may be challenging to measure some aspects of human performance. In particular, methods for measuring the degree of operator complacency and skill degradation should be identified. Operator complacency can be regarded as the level of operator lack of suspicion on the state of automation. Thus, complacency can be determined based on comparison of actual performance results with operator subjective ratings. Skill degradation can be quantified in terms of time to error recovery following an automation failure (Parasuraman et al., 2000)

or time for mental reorientation to an automation state change in using an adaptive system. To develop a practical automation cost model, the level of skill degradation can be measured by collecting empirical data of manual skill decrements for error recovery or reorientation over time. Applicable measures of SA, system output, and errors may already exist and have been frequently used in the other domains.

We have developed this quantitative model of automation considering life science systems; however, the model may be limited in application to other types of systems with different characteristics and demands on human operators. Use of such a model will ultimately provide more systematic insight into the effects of various LOAs on complex system performance than a qualitative modeling approach may afford.

5. CONCLUSION AND FUTURE RESEARCH

The life sciences domain presents complex applications for robotics and automated measurement technologies. Existing automation strategies have been motivated by high demands for new drug development processes and the need for high volume screening analytics and screening of molecular reactions. The historical approaches to LSA have been largely technology centered and have, to some extent, overlooked major changes in the roles of human operators and the potential implications of automation on human performance, as discussed by Parasuraman et al. (2000).

Future research needs regarding life science process design concern achieving even higher degrees of parallel operation and lower sample volumes while maintaining accuracy and speed in analytics and/or screening. For example, dynamic operation scheduling capabilities need to be developed for process control to facilitate maximum automated device utilization in real time. This may be critical for laboratories that are under high demands for screening results. Beyond this, there is a need to establish a strategy for dynamic scheduling in multiprocess scenarios and resource management.

In specifying new LSA strategies, like this, there is a need for application of HCA theory and modeling approaches to promote design for safe and effective system operations as well as the quality of operator work life. Empirical investigations should be conducted to classify new forms of LSA in terms of existing theories and to assess human performance consequences of specific automation designs in terms of errors, workload, and SA. In addition, qualitative and quantitative modeling approaches, such as those presented earlier in this article, should be applied for projecting the implications of specific forms of automation on operator performance. Recommendations of design guidelines for new system functions allocation schemes should be made to optimize human and machine performance. This approach could also be extended to other domains requiring strategic function allocation between humans and automation in complex systems control, such as nuclear power plant processes and air traffic control systems.

Another method for dealing with automation usability issues in the life sciences domain is to attempt to optimize human interface design. For example, user-friendly devices and integrated data management capabilities, based on LIMS, are needed to support operator tracking of high numbers of samples during methods. Also, such capabilities are needed for process data visualization and analysis, particularly in HTS applications. The human interfaces as part of contemporary LSA systems need to facilitate operator method programming, monitoring of automated device states, resolution of system faults, and collection, inspection, and storage of process data. Several commercial software manufacturers have developed applications for automated method programming (e.g., the SAMI®; Beckman

Coulter, Fullerton, CA). This software allows a biochemist to develop graphical models (resembling flow charts) of chemistry or biological experiments to be conducted using integrated robotic and automated systems. The main design issue with such software is that programming is focused on selecting and setting device parameters for processes versus describing the experimental processes and relying on the system to identify appropriate equipment and settings for execution. For some biochemists, this approach to method programming may be less intuitive than benchtop process specification. There is a need for human factors research to develop new human–machine control interfaces for contemporary LSA that are focused on operator specification and management of processes versus devices. Some progress has been made already in this area (e.g., Kaber, Segall, & Green, 2007) through the use of metaphor-based interface design for HTS systems. Beyond this, there is a need to develop interfaces that provide the right information to operators at the right time to reduce the number of displays that must be used and to monitor workload. Additional research is needed in this area to prototype and test interfaces for human performance improvements. As with new forms of automation, recommendation of design guidelines for new LSA interfaces should also be developed.

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