15.1 Introduction

Use of digital human models in computer-aided engineering has increased rapidly over the past 10 years (Chaffin, 2001; Sundin & Örtengren, 2006). Such models typically take into account anthropometric and biomechanical characteristics of humans, allowing a designer to develop a visual, physical model of the human, called a mannequin. The digital human can be placed in computer-generated environments of various types and programmed to carry out specific tasks that require interacting dynamically with products, systems, or workspaces. The designer receives direct visual feedback and summary data concerning whether the design is adequate to accommodate human users of various sizes, and can modify design properties until an acceptable degree of accommodation is attained. For example, Karim Abdel-Malek, director of the Virtual Soldier Research program at the University of Iowa, recently said of the digital human Santos™, We can ask Santos to change an oil filter on a dump truck or some similar task. As he goes about doing the job, we can query any part of his body functions, such as heart rate, temperature, muscle load, and others. At the same time, we can watch him work onscreen and observe any problems he might encounter. (quoted in Hudson, 2006)

For the most part, with Santos being an exception (Virtual Soldier Research, 2004), digital human modeling has focused primarily on the physical attributes of people (e.g., Sundin & Örtengren, 2006). Although there are many technical issues regarding the techniques used to generate human motion to carry out various tasks, the models are relatively successful at depicting the physical interactions of humans and products/systems. However, several authors have noted a need to model human cognitive characteristics as well (e.g., Badler, 2000). As an example, although Sundin and Örtengren (2006) focused their review of digital human models on simulation of physical attributes, they initially defined digital human modeling as involving cognitive functioning as well: “In the attempt to represent the complex human being digitally, functions being modeled include both physical and cognitive performance human aspects” (p. 1054). Bubb (2002) earlier made the point, “Modeling cognitive behavior will
become more and more important as the technical design of machines demands a lot of human information processing abilities” (p. 252). Thus, there is a need to combine human cognitive models with anthropometric digital human models to simulate the full range of human performance.

Sundin and Örtengren’s (2006) stated reason for focusing exclusively on physical simulation was simply, “Compared to the area of physical modeling, the area of cognitive and performance modeling is not as well known or developed” (p. 1055). However, although cognitive and performance modeling has not been integrated into physical digital human modeling and may not be well known to digital human modellers, a wealth of literature on cognitive and performance modeling exists outside of the domain of digital humans (Fisher, Schweickert, & Drury, 2006; Laughery, Lebiere, & Archer, 2006). This literature includes complete models of cognition and performance developed within unified cognitive architectures (e.g., Byrne, in press), as well as more detailed models built to explain specific aspects of cognition (e.g., attention; Logan, 2004). Thus, cognitive and performance modeling is in fact relatively well developed.

An essential aspect of cognitive and performance modeling for digital humans in many situations is to model the speed and accuracy of their choice behavior. For example, Bubb (2002) stated, “Especially the opportunity to precalculate … the reaction behavior, for example, at what time what buttons are operated, can serve as forcing function for the appropriate movement of head, upper body, and extremities” (p. 263). Consequently, the present chapter focuses on ways to model response time (RT) and accuracy for digital humans in situations where rapid choices among alternative actions must be made. We review work on predictive models of RT and accuracy, with an emphasis on those models that distinguish information accumulation from thresholds for responding based on that information.

15.2 Stage Analysis of the Cognitive System

Since the 1950s, the human information-processing approach has been dominant in cognitive psychology (Proctor & Vu, 2006a). According to this approach, human cognition can be viewed as the product of processes that operate on information provided by the sensory systems. Modeling techniques developed in the context of the information-processing approach include Soar (Newell, 1990), ACT-R (Anderson & Lebiere, 1998), and EPIC (Meyer & Kieras, 1997). These techniques analyze the cognitive system into functionally distinct modules, such as the sensory, motor, and central processing systems, and simulate human performance through the dynamics of a general cognitive architecture. Thus, with the information-processing approach, human cognition is viewed as a dynamic system that consists of several subsystems, each of which has a specific function to interact with the environment.

The root of the techniques for analyzing the cognitive system into distinct subsystems can be traced back to the studies of Donders (1968/1969). Donders was concerned with measuring durations of mental processes. He reasoned that different tasks require distinct mental processes, and that RT should reflect the durations of the processes involved in those tasks. Suppose, for example, one performs two different tasks, Task 1 and Task 2. Task 1 is known to involve mental processes A, B, and C, whereas Task 2 involves mental processes A and B. Then, the duration of C can be obtained simply by subtracting the RT for Task 2 from that for Task 1. Thus, this technique is called the subtractive method (Sternberg, 1998).

The subtractive method has been applied not only to RT in behavioral studies but also to measures of brain activity in neural imaging studies (Newman, Twieg, & Carpenter, 2001). With techniques such as functional magnetic resonance imaging (fMRI), brain activity occurring while people perform tasks can be monitored. It is by using the subtractive method that experimenters identify brain regions that are more active during one task than others and link the regions to cognitive processes uniquely involved in performing the task.

With the subtractive method, however, cognitive processes and functions of brain regions can only be inferred based on a separate analysis of the tasks that are compared. Disagreement about the component
processes of tasks can lead to questions about the validity of conclusions drawn using the subtractive method. For instance, Donders’ (1968/1969) original study provoked a criticism from Wilhelm Wundt, the founder of experimental psychology, on Donders’ speculation about the mental processes involved in one of three tasks, called a c-reaction (or go/no-go task; Johnson & Proctor, 2004). For this task, an observer is to respond to one stimulus but withhold responding to another. Donders compared RT for c-reactions to that for a-reactions (or simple reaction tasks), in which an observer is always to make a response to a stimulus presentation, and considered the RT difference to reflect a stimulus-identification process. Wundt criticized Donders’ assumption, and hence his interpretation, arguing that c-reactions also involve choice between responding or not responding (i.e., a response-selection process). This example illustrates the importance of task analysis for applying the subtractive method.

Sternberg (1969, 1998) elaborated on the subtractive method to provide a means for determining whether two variables affect task processing at a single stage or two distinct stages. Such variables include, for example, figure-ground contrast, number of alternative choices, stimulus duration, and stimulus-response compatibility. With Sternberg’s method of additive factors analysis, additive effects of two variables indicate that the variables influence different stages in the processing sequence, whereas interactive effects suggest that the variables may influence the same stage.

Suppose that the experimenter orthogonally manipulates two factors involved in a task. If the sum of the increase of RT for increases in difficulty of each variable alone is equivalent to the increase of RT for simultaneous increases in difficulty of the two variables, the effects are additive and indicate that the two factors may prolong separate processing stages. In contrast, if the sum of the increases of RT for increases in difficulty of each variable alone is less than the increase of RT for simultaneous increases in difficulty of the two variables, their effects are interactive and indicate that the factors may affect the same processing stage.

In contrast to Donders’ subtractive method, the additive factors analysis involves manipulations of levels of multiple variables involved in a task. It presupposes that cognitive processes for a task are not qualitatively altered by manipulating levels of variables but that there are only increases or decreases of processing durations. On the other hand, additive factors analysis does not identify functions of processing stages directly but only indicates whether factors have a stage in common or not. Hence, the function of a processing stage has to be inferred from the variables that affect that stage. Nevertheless, application of additive factor analysis allows stages to be discovered that have not been recognized previously. By manipulating multiple factors, one can find factors that are additive to each other, and the number of those factors is equivalent to the minimum number of processing stages involved in the task. Then, one can assign descriptive labels to those processing stages based on the nature of the variables that interact.

Sanders (1998), a proponent of additive factors analysis, has used the method extensively and proposed six robust stages: preprocessing, feature extraction, identification, response selection, motor programming, and motor adjustment. According to his analysis, several factors modulate those processing stages. For instance, figure-ground contrast predominantly prolongs the preprocessing stage, whereas signal quality has a major influence on the feature-extraction stage. Moreover, stimulus-response compatibility seems to affect the latency and accuracy of the response-selection stage (see, e.g., Proctor & Vu, 2006b). In contrast, other factors, such as signal frequency and the number of alternative choices, tend to interact with several environmental factors, suggesting that they affect multiple stages of information processing. Thus, additive factors analysis is useful in modeling RT in complex situations because, by analyzing environmental factors involved in tasks, one can consider how manipulations of those factors should be treated in models of task performance.

Both the subtractive and additive factors methods assume that the cognitive processes involved in performing a task are arranged in a sequence of discrete stages. Thus, if the times for each individual processing stage can be estimated, total response time can be predicted simply by summing the times for the component processes. This is how predictions are derived using the model human processor, a simplified information-processing framework developed by Card, Moran, and Newell (1983) of which
most human factors and human-computer interaction professionals are aware: Time to perform basic tasks can be predicted by adding the times for component perceptual, cognitive, and motor operators determined from a task analysis.

However, the physical substrate of the cognitive system is the nervous system, which consists of a massive network of interconnected neurons where activities involve enormous parallelism. This structure suggests a need to consider models in which two or more cognitive processes proceed concurrently. Schweickert’s (1978, 1984) latent network theory extends the additive factor analysis to apply to those situations. In particular, Schweickert demonstrated that when a network of cognitive processes allows some processes to be concurrent, the difference between RT for prolonging two processes and the summed RT for prolonging each process individually indicates whether the processes are performed concurrently or serially in the network. For instance, subadditive interaction of two variables, a smaller RT for the condition in which two variables are manipulated simultaneously than the sum of RTs for the conditions in which they are manipulated separately, indicates that these factors are processed concurrently.

Similarly, Dzhafarov and Schweickert (1995) developed a more general theory of testing RT components. As in Sternberg’s additive factor analysis and Schweickert’s latent network theory, RT is seen as reflecting properties of cognitive processes that are selectively influenced by specific environmental factors, such that, for example, additivity of two factors can be expressed as $RT(\alpha, \beta) = A(\alpha) + B(\beta)$, in which A and B are component times dependent on levels of factors $\alpha$ and $\beta$, respectively, and $\alpha$ indicates the equivalence of the distributions of the left and right sides of the equation. In other words, RT can be decomposed into two component times whose relation is expressed by an algebraic operation, such as addition (+), minimum, or maximum. These operations are called decomposition rules. By applying Dzhafarov and Schweickert’s decomposition tests (under certain assumptions), a unique decomposition rule can be recovered from the observed RT distribution. Once a decomposition rule can be identified, the architecture underlying the RT distribution can be interpreted.

Details of the latent network theory and the decomposition theory are beyond the scope of the present chapter. Interested readers can consult Schweickert (1978) and Townsend and Ashby (1983) for the latent network theory, and Dzhafarov and Schweickert (1995) and Van Zandt (2002) for RT decomposition theory. Also, applications of the decomposition theory and its statistical test are discussed by Cortese and Dzhafarov (1996) and Dzhafarov and Cortese (1996).

For modeling purposes, it is relatively easy to manipulate and add parameters arbitrarily to fit a model to observed RT patterns. However, a good fit of model outputs to experimental data obtained from human performance does not necessarily guarantee the validity of the model. Thus, it is important to construct RT models based on known facts about the behavior of the cognitive system (Proctor, 1986). Stage analysis offers a way to experimentally investigate what types of processing stages are involved in the task, how environmental factors affect such stages, and what structure they should be considered in the models. Consequently, stage analysis provides a fruitful basis for quantitative formulations and modeling of the cognitive system.

### 15.3 Accumulation Models of Response Times and Accuracy

As introduced in Chapter 32 of this volume, ACT-R (Anderson & Lebiere, 1998) is one of the cognitive modeling environments that has been applied to a wide variety of human decision tasks. ACT-R models are based on a general cognitive architecture, of which a central component is spreading activation throughout the memory network (Anderson, 1976, 1995). The speed and probability of retrieving a particular piece of knowledge are determined by the activation of a node in the network that represents that knowledge. The assumption is that a memory or chunk is retrieved only if its activation exceeds threshold. This mechanism of selection postulated in ACT-R resembles a more general family of mathematical

Whereas activation in ACT-R is concerned primarily with interconnectivity in the network space (the number of nodes connected to the target node and their associative strengths), sequential sampling models employ activation of responses that is dependent on a temporal function of the evidence accumulation process. In sequential sampling models, a decision is made when sufficient evidence in favor of one of the alternative choices is collected. The collection of evidence is represented as a temporal process of sampling from the available source of information (say, a stimulus representation) \( S \) that is associated with one of the alternative choices \( R \). The decision process is terminated and response is made when the accumulating evidence \( U \) exceeds a pre-specified response criterion, or threshold, \( \theta \).

Sequential sampling models assume that the stimulus representations from which each sample is drawn (or communication paths through which the stimulus information is conveyed) are noisy, an assumption that has been adopted widely since development of information theory (Attneave, 1959; Shannon & Weaver, 1949) and signal detection theory (Swets, Tanner, & Birdsall, 1964). This assumption of noisy representation provides a critical basis for the stochastic nature of the models. In classic signal detection theory, for instance, a stimulus representation is often assumed to have a normal distribution with mean \( \mu \) that represents the true value associated with the stimulus and variance \( \sigma \) that is attributed to the background noise. A sample is represented as some psychological value \( X \), which can arise from noise alone or the combined effect of the stimulus representation and the background noise. Thus, whether or not the sample comes from the stimulus representation \( S \) is probabilistic. Consequently, the confidence level of the decision is closely related to the likelihood ratio \( p(x)/q(x) \), where \( p(x) \) is the conditional probability of obtaining \( x \) from the combined effect of the stimulus representation and noise (correct sampling), and \( q(x) \) is the conditional probability of obtaining \( x \) from noise alone (incorrect sampling).

Let us suppose a simple case of decision making, two-choice reaction tasks in which the stimulus \( S_A \) or \( S_B \) is presented and the associated choice \( R_A \) or \( R_B \) is selected. In a type of sequential sampling model, called the random walk model (Laming, 1968; Stone, 1960), the selection process is terminated and \( R_A \) is selected when \( U_n > \theta \) or \( R_B \) is selected when \( U_n < -\theta \). In other words, the random walk process is represented as the amount of accumulating evidence plotted against the time axis (see fig. 15.1). Though the model can be adapted to situations for which more than two choices are available by representing the accumulation process as a point moving in a multidimensional space (Laming, 1968), here we will focus on the cases of two-choice alternatives for simplicity.

![FIGURE 15.1](image-url) Illustration of a typical random walk process.
According to the random walk model developed by Laming (1968), RT corresponds to the time to attain either of the response criterion value, \( n_h \), where \( n \) is the number of samples and \( h \) is the time interval between two samplings. Generally, the random walk process is expressed as

\[
U_n = U_0 + \sum_{i=0}^{n} v_i,
\]

where \( U_0 \) is the initial state of the decision process and \( v_i \) is the increment of evidence at the \( i \)th sampling. The increment \( v \) is a specific value of a random variable \( V \), corresponding to the confidence level and defined as the log-likelihood ratio, \( V = \ln[p(x \mid S_A)/p(x \mid S_B)] \) (Laming, 1968; Stone, 1960), such that \( x \) is a specific value of a random variable \( X \) that takes values, \( x_1, x_2, x_3, \ldots, x_n \). Thus, \( x_i \) is the \( i \)th value of sampling. The conditional probability \( p(x \mid S_A) \) is a probability of obtaining \( x \) given that the stimulus \( S_A \) is presented, and \( p(x \mid S_B) \) is a probability of obtaining \( x \) given that the stimulus \( S_B \) is presented. The distribution of \( X \) is assumed to be symmetric with mean \( \mu_A \) (\( \mu_B \)) and variance \( \sigma_A^2 (\sigma_B^2) \), representing the stimulus \( S_A (S_B) \) (see fig. 15.2). The increment \( V \) is then given by

\[
V = \ln \left[ \frac{(2\pi\sigma_A^2)^{1/2} \exp\left\{ -(X - \mu_A)^2 / 2\sigma_A^2 \right\}}{(2\pi\sigma_B^2)^{1/2} \exp\left\{ -(X - \mu_B)^2 / 2\sigma_B^2 \right\}} \right].
\]

Note that the variances \( \sigma_A^2 \) and \( \sigma_B^2 \) represent the background noise confounded with the actual stimulus representations \( \mu_A \) and \( \mu_B \). Therefore, they are assumed to be equal, \( \sigma_A = \sigma_B = \sigma \), and the expression can be rewritten as

\[
V = \frac{\mu_A - \mu_B}{\sigma} \left( X - \frac{\mu_A + \mu_B}{2} \right) \cdot
\]

It is important to note that \( V \) is expressed in terms of two concepts that are central to signal detection theory (Swets et al., 1964); the discriminability of two signals, \( d' = (\mu_A - \mu_B)/\sigma \), and the optimal criterion for the detection process, \( \beta = (\mu_A + \mu_B)/2 \) (note that here we use the detection criterion \( \beta \) in the detection process that is different from the response criterion \( \theta \) in the accumulation process). Thus, the above equation can be rewritten as

\[
V = d' \frac{X - \beta}{\sigma} \cdot
\]

In effect, the increment of evidence \( V \) can be interpreted as the standardized distance of the observation \( X \) from the optimal criterion \( \beta \) weighted by the discriminability \( d' \) between the two stimuli. Thus, the increment will be greater when the observation is closer to either extreme of the partially overlapped distributions representing the stimuli. Hence, it is clear that in the random walk model, the decision process consists of a number of discrete detection processes over time.

It often appears that human decision making is biased to favor one choice over the other. A bias may reflect the situations, for example, in which one choice occurs more frequently than the other, more successes to accomplish one’s goal have been attained with one choice than the other, or more costs are associated with one choice than the other. There are two ways to incorporate a decision bias into a random walk model. The first is a bias that is represented by the initial state of the decision process. More specifically, \( U_0 > 0 \) is a bias favoring choice \( R_A \) and \( U_0 < 0 \) choice \( R_B \). Similarly, while adopting the initial state at the origin, response criteria for the two choices can be varied, such that \( \theta_A = \theta + \alpha \) and \( \theta_B = -\theta + \alpha \), to produce equivalent processes.
The second way to incorporate response biases is to allow the detection criterion $\beta$ to shift. As in the above equation, placing the criterion for the detection process at the midpoint between the means of the two distributions, $\mu_A$ and $\mu_B$, is optimal when all factors other than the means are identical for $S_A$ and $S_B$. However, the optimal criterion can be shifted closer to either extreme as the probabilities and costs associated with $S_A$ and $S_B$ differ (Swets et al., 1964). Thus, if $\beta$ shifts toward $\mu_B$, the choice $R_A$ is more likely chosen throughout the trials, whereas the choice $R_B$ is more likely if $\beta$ shifts toward $\mu_A$. The general tendency for evidence to accumulate for one choice over the other is called the drift rate and reflected in the mean of increments within a trial.

In random walk models, the accuracy of a response on a particular trial is dependent primarily on the probabilities of correct and incorrect sampling $p$ and $q$ in the detection process. That is, if one sample is needed for response selection, the probabilities of correct response $P$ and incorrect response $Q$ are equal to $p$ and $q$, respectively. On the other hand, when multiple samples are required to make a response, the response accuracy improves such that $P/\theta > Q/\theta$ and $Q/\theta > Q$. In other words, as the value of the response criterion $\theta$ increases and more samples are required, the latency and accuracy of responding also increase (Townsend & Ashby, 1983). In this way, the model is able to account for speed-accuracy trade-off (e.g., Vickers, 1970).

However, this property also yields a problem for random walk models. Namely, the models predict perfect accuracy if a sufficient time is allowed to select a response, which is not consistent with empirical observations (Ratcliff & Smith, 2004). To eliminate this problem, Ratcliff (1978) introduced an assumption that, depending on the relatedness of the alternative choices, the drift rate varies from trial to trial due to input perturbations. The between-trial variability is expressed as the standard deviation of the drift rate and termed the diffusion coefficient. Ratcliff’s version of random walk model is a specific version of diffusion process model, which is in turn a random walk model modified as a continuous time function $t$. Ratcliff’s diffusion process model is considered one of the most powerful models for choice behaviors (Logan, 2004).

Another class of sequential sampling models is called the counter model (LaBerge, 1962; Pike, 1973; Townsend & Ashby, 1983; Van Zandt et al., 2000) and the accumulator model (Usher & McClelland, 2001; Usher et al., 2002; Vickers, 1970; Vickers et al., 1971). The major difference of counter models from random walk models is that, whereas random walk models assume a single accumulation process for multiple alternative responses, in which evidence for one response is taken as negative evidence against others, counter models assume independent and parallel accumulation processes, each of which corresponds to one of the response alternatives. According to a counter model developed by Pike (1973), the evidence accumulation process is represented as counting discrete signals. The counters increment 1 for the arrival of a signal, and response is made when the count for either choice accrues to a pre-specified response criterion. It is generally assumed that the arrival time of a signal is exponentially distributed, and thus the decision process can be viewed as a race between independent and parallel Poisson processes (Pike, 1973; Townsend & Ashby, 1983).
Similarly, the accumulator model assumes separate accumulators associated with alternative choices. On the other hand, whereas the counter model employs integer-valued increments of counts with exponentially distributed time intervals, increments of evidence in the accumulator model are a real-valued random variable. In a general version of the accumulator model (Vickers, 1970; Vickers et al., 1971), evidence is accumulated at equally spaced time steps and the amount of increment in an accumulator varies at each step. A more recent version of the accumulator model exploits a continuous temporal function of accumulation process (Usher & McClelland, 2001).

It is normally observed that increasing the number of alternative choices tends to slow the overall latency of responding. In such a condition, RT is modeled as a logarithmic function of the number of response alternatives, called Hick’s law (Hick, 1952). The accumulator model can account for the observation with increase of response criterion $\theta$, which reflects one’s decision confidence (Vickers & Lee, 2000). In addition to this approach, Usher and McClelland’s (2001) connectionist-based model devised lateral inhibition, the mechanism that an excitation of an accumulator produces inhibitory inputs to other accumulators. That is, the more response alternatives that are involved in the task, the more inhibitory inputs an accumulator receives. These models exemplify the flexibility and generality of the accumulator model in applying to various task settings.

Finally, Dzhafarov (1993) provided an argument on sequential sampling models that is potentially important in applying the models in complex task settings. According to his formal analysis, any stochastic accumulation model can be translated into a model that employs a strictly increasing, deterministic accumulation process and variable response thresholds, a type of model represented by Grice’s (1968) variable criterion theory. In such models, the accumulation process is conceptualized as deterministic and the response criteria are represented as random variables. Brown and Heathcote (2005) recently demonstrated that Usher and McClelland’s (2001) accumulator model can be modified as a similar deterministic model, which involved variable initial states as well as variable criterion values, and argued that the deterministic process model maintains performance at the same level as the original model and other stochastic accumulation models such as Ratcliff’s diffusion process model. They agreed with Dzhafarov’s conclusion that by using deterministic processes, sequential sampling models can be made simpler and more analytically tractable.

Whereas the modeling schema discussed in this section has been developed to account for simple choice behaviors, it should be emphasized that the schema has great flexibility to encompass a broad range of human cognitive tasks. For instance, Vickers and Lee (1998, 2000) constructed a neural network that takes an accumulator model as its basic unit. Similarly, Busemeyer and his colleagues (Busemeyer, 1985; Busemeyer & Goldstein, 1992; Busemeyer & Townsend, 1992, 1993) have developed the decision field theory of deliberative behavior in which a serial sampling process is embedded. These models provide examples of sequential sampling models to capture human performance in a more complex environment.

15.4 Conclusion

RT and accuracy of responses have been the two measurements of human cognitive performance that are most widely used in experimental psychology. Simulating these measurements is to reverse the procedures of theory construction. Thus, it is important in simulating RT and accuracy of human performance to be acquainted with assumptions involved in the procedures used to analyze experimental studies of human cognition. To this end, we reviewed modeling frameworks that have been studied and used extensively in psychological research and are of interest in simulating digital humans. It is not possible within a limited space to discuss more detailed mathematical properties associated with the modeling techniques. We thus recommend that interested readers consult respective references for further examination of the techniques.

As emphasized in this chapter, sequential sampling models have sufficient flexibility and can be useful components as the basis of more sophisticated cognitive models in digital human modeling.
Similarly, processing stage models offer a theoretical basis for cognitive processes and structures, based on which modelers can decide which parameters should be manipulated in given task settings. It was also emphasized that cognitive processes and functions in such models have to be specified by analyzing the task of interest. There are modeling tools (e.g., MicroSaint and GOMS) that adopt approaches to human performance based on task analysis (e.g., John, 2003; Laughery & Scott-Nash, 2000). These tools may be useful for the purpose of model specification.

Finally, though the decision process that sequential sampling models depict is a central aspect of all cognitive behaviors, digital human modeling needs to incorporate detailed perceptual and motor processes to simulate more complete human performance. Fortunately, theories and models of these processes are being continually developed in domains that are very active in psychological research. What is needed, then, is to choose, and perhaps combine, appropriate models that are suited to the relevant aspects of the tasks and environment in which human performance of digital humans is modeled. As in MIDAS and IMPRINT (e.g., Mitchell, 2003; Tyler, Neukom, Logan, & Shively, 1998), combined use of those different approaches may be valuable in the development of modeling environments for digital humans.

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Modeling Response Time and Accuracy for Digital Humans


