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Trajectory of Cognitive Science and Psychological Assessment: Current Status and Expectations

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Salient commonalities and distinctions of the set of contributions to this special section are synthesized and discussed. The examination provides a springboard for observations on future developments in cognitive-science applications. Issues considered include imminence and nature of clinical implementation, prediction of selected client transactions outside the assessment context, integration with complementing modes of clinical assessment, and reciprocal information sharing by clinical and nonclinical cognitive scientists.

This discussion highlights certain commonalities among the represented cognitive-science applications and indicates some anticipated directions of future work. The enumeration somewhat addresses a special-section mandate of providing a status check on assessment-relevant developments within the topic domain and is combined with a tendered forecast of new opportunities.

Logistics of Clinical Implementation

An issue bearing on the appropriation of cognitive-science-based assessment strategies is that of feasibility of implementation. The latter entails exigencies of the applied setting, including the cost and time of procedures that convey information about single individuals. In some instances, assessment methods may comprise upward of 100 trials of cognitive-paradigm performance.

Such requirements may appear at first blush to be onerous and inordinately time consuming. In fact, however, they are often substantially less taxing than many procedures in common usage. For example, 100 trials of an information-processing task with 1- to 3-s intertrial intervals, can take no more than 26 min to complete. In contrast, some prominent inventories involve several hundred items, and certain structured interviews can be highly resource intensive with respect to time and personnel.

Turning to clinical utility, the current array of contributions varies both in directness and in the nature of client-level inferences. In selected instances, procedures are appropriated to the individual (Siegle & Hasselmo, 2002) and are accompanied, moreover, by normative distributions of substantively significant model-parameter values to which estimates in the immediate case can be directed (Busemeyer & Stout, 2002). Client-specific procedures are illustrated in the application of connectionist modeling (entailing networks of multiple simple processors, analogous to systems of neurons in the brain). Siegle and Hasselmo (2002) customized modeling to simulate individual symptomatology by calibrating selected model properties according to preliminary psychometric measures. Person-specific procedures are also seen in analyses of debility in decision and choice that use a convenient card-selection paradigm (Busemeyer & Stout, 2002). Individualized estimates of each performance-model parameter (expressing motivational, learning, or response aspects of choice behaviors) provide for normative distributions of the respective parameter values.

In other instances, combining data sets from multiple participants represents the currently available means of ensuring reasonably noise-attenuated stable estimation of performance-model features (Treat et al., 2002). In such cases, however, inferences to any one person are still possible by ascertaining that the individual at hand corresponds to members of the relatively homogeneous collective to whom evaluated model features apply. A blueprint to extend applications more directly to individuals is nonetheless in place (Treat et al., 2002).

In generalizing group estimates of model properties to individual participants, it is naturally assumed that group-level findings are reasonably representative of the individual case. A necessary corollary is that the modeled data not be an amalgam of systematic individual differences in model properties. Agglomerating consistent differences in model expression creates a risk that group-level results will fail to satisfactorily depict any one of the group's constituent enclaves. This type of barrier to individual-level generationalization has been examined in detail elsewhere (e.g., Luce, 1997; Neufeld & Gardner, 1990; Riefer, Knapp, Batchelder, Bamber, & Manifold, 2002), as have methods of ascertaining the necessary homogeneity of constituent data protocols (Carter, Neufeld, & Benn, 1998).

A received method of reducing the demands of obtaining information ordinarily educed through extensive inventories or structured interviews is to use abbreviated screening devices (Antony & Barlow, 2002; Derogatis & DellaPietra, 1999). Such methods provide psychometric data that typically are acknowledged as less exact than those delivered by their parent formats.

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A somewhat analogous but distinct procedure embraces Bayesian techniques (Neufeld, Vollick, Carter, Boksman, & Jetté, 2002). In estimating a model property (e.g., parameter) for the individual, existing information is imported from the property's assumed distribution among the individual's group (i.e., its prior distribution). This information is combined with the person's performance on the modeled cognitive task by applying Bayes's theorem. Only a modest sample of cognitive performance may be required to attain reasonable estimation accuracy (i.e., approximation of true values, with associated temporal stability and diminished dispersion; Marriott, 1990; see also Haynes & O'Brien, 2000).[1] The boost in accuracy is obtained through the information afforded by the prior distribution, incrementing that provided by the immediate performance data and issuing in the more precise (more narrow) Bayesian posterior distribution.

Customary screening measures usually sacrifice precision because of their brevity as preliminary devices, over and against subsequent, more comprehensive measurement formats. Bayesian analysis of a trimmed-down pool of observations arguably preserves or potentially increases accuracy of model-property estimation over that available even from elongated cognitive-paradigm administrations. The potential accuracy is tapped, then, by formally integrating the bank of information already on hand with that supplied by the individual's performance specimen. Furthermore, Bayesian estimates bring with them quantified errors of estimate, according to variances of the client-adapted posterior distributions from which the parameter estimates (e.g., posterior-distribution means) themselves are derived. The upshot is that Bayesian methodology, in principle, brings into play the convenience of screening devices but without the need to defer accuracy pending more extensive measurements.

As with values from other estimation methods, Bayesian-based estimates can be located within normative distributions of parameter values (Busemeyer & Stout, 2002; Treat et al., 2002). It is interesting that the role of the normative distribution of parameter values in effect can be served by the relevant Bayesian prior distribution, as described above.

All things considered, implementation of these developments raises the prospect of monitoring cognitive performance, including treatment-induced changes, in a rigorous cognitive-science-principled manner (McFall & Townsend, 1998). Ever-expanding computational capacity and speed of office computers, along with contemporary software developments, should accelerate the readiness of nascent technology bestowed by the type of contribution found here. Indeed, the following speculation seems less than chimerical, even for the near future: Computer-administered cognitive paradigms will engender personalized profiles of parameters and other model features, which will be interpreted against selected normative distributions (corresponding to typical standardization tables), and will predict variables bearing on clinical intervention and prognosis.

Integration of Complementing Forms of Analysis

The current implementations of cognitive-science paradigms address clinical problem areas ranging from sexual aggressiveness to schizophrenia, each approached with its own modeling strategy. It seems reasonable that clinicians will wish to avail themselves of more comprehensive assessment information on a given presenting problem, information arising from integration of a multiplicity of techniques. Stochastic model applications (Busemeyer & Stout, 2002; Neufeld et al., 2002; Treat et al., 2002) stand to be complemented by those of connectionist modeling (Siegle & Hasselmo, 2002) and, for that matter, by affiliated nonlinear dynamic systems methods (e.g., in the popular vernacular, *chaos theory*; Haynes, 1995), of which selected connectionist approaches might be regarded as a subset (Townsend, 1994).

There is precedent in the field of cognitive science for delineating a specific domain (decisional process) according to cognitive mechanisms described by stochastic modeling (Busemeyer & Stout, 2002; Busemeyer & Townsend, 1993), connectionist modeling (Roe, Busemeyer, & Townsend, 2001), and nonlinear dynamic systems theory (Townsend, 1992). In clinical cognitive science, the nature of cognitive deviation can be deciphered through parallel titrations of stochastic and connectionist models (Carter, 2000; Carter & Neufeld, 1999; 2002), with theoretical extensions to negotiation of stressing environmental demands aided by nonlinear dynamic systems and by other more molar modeling strategies (Lees & Neufeld, 1999; Neufeld, 1999a).

Each orientation can provide insights sui generis to its own level of analysis (Marr, 1982), thus contributing to the collective clinical characterization of the individual. The present and related approaches (e.g., Batchelder, 1998; Chechile & Roder, 1998; Riefer et al., 2002) seem poised for use in clinical cognitive assessment, individually or in tandem, and specific illustrations hopefully will seed their broader usage.

External Validity

An important mandate of the assessment enterprise, of course, entails drawing valid inferences about functioning outside the measurement setting. In league with this goal, the formal frameworks from which the present versions of cognitive assessment proceed can lend added insight into the ecological significance of discerned strengths and weaknesses. Models created within the cognitive science framework require formal accounting for aspects of the environment.

Breaking down person–environment transactions into simple axioms reminiscent of formal game theory (cf. Blackwell & Girschick, 1979), for example, can highlight cognitive processes involved in securing physical and social safety. Quantifying a certain give-and-take with the individual's surroundings, in other words, should unveil cognitive undertakings mediating successful resolution of demands and stresses. It follows that the profile of cognitive frailties undermining environmental transactions is thrown into relief.

Negotiating environmental demands and stresses carries a cognitive load; ascertaining a desired course of coping action entails the processing of information about eligible options. A prominent form of coping known as *decisional control* (Averill, 1973), for example, involves positioning oneself in a multifaceted stressor situation so as to minimize the probability of a socially or physically aversive event (Neufeld, 1990). Option-related predictive

[1] Screening procedures presumably render appreciable psychometric sensitivity and negative predictive power; accuracy, as qualified here, of course, stands to improve specificity and positive predictive power as well.

judgments about such threats, underlying informed coping action, implicate memory search, visual scanning, and information synthesis (e.g., Kukde & Neufeld, 1994; Paterson & Neufeld, 1995).

Rudimentary properties of decisional control can be used to formulate situational prototypes that vary in prevalence and in requirements of threat-reducing choice (Morrison, Neufeld, & Lefebvre, 1988; Neufeld, 1999b). These prototypes now comprise a staging ground for quantitative derivations expressing the interplay among key variables of decisional control. It can be shown that situational properties affording an increased measure of control are accompanied by a gauged amount of potential threat reduction (reduction in probability of aversive incident occurrence). Minimizing threat, in turn, is predicated on the assembly of a strategic corps of predictive judgments that make for advantageous selection. Together, such developments allow for a formal context in which to place impairment of the cognitive faculties that are called on to deal with stress and thereby help elucidate the nature of coping deficit.

Apart from issues of environmental stress negotiation, increased opportunities for extension of developments in cognitive science to clinical assessment take the form of monitoring the state of cognitive performance over the course of clinical treatment. Pharmaceutical treatments, for instance, more than ever are being evaluated according to clients' ongoing efficiency of mentation, an approach that supplants the earlier emphasis on measured quality of life. The present offerings point to an ever-increasing arsenal of cognitive-science grounded tools for detecting subtle variants in cognition (see McFall & Townsend, 1998, for an indictment of overreliance on off-the-shelf measures of cognitive faculties). It is interesting that, as intimated above, assessment methods represented in this section, in principle, can leverage life-quality implications of their own, through their connection to quantitative prototypes involving stress, coping, and related processes.

Contributions to Other Levels of Assessment

Results from formal cognitive assessment stand to enhance information from other levels of measurement, such as functional magnetic resonance imaging (fMRI) of brain-activation patterns. Cognitive assessment methods can point to key epochs of fMRI output, as determined by modeled cognitive events. They can do so by indicating periods within task trials in which target cognitive functions tenably are present. Imaging measures, in turn, can be synchronized with the delineated functions' chronotropic effects on MRI-indexed brain activation (Neufeld et al., 2002; Siegle & Hasselmo, 2002).

Recent developments in fMRI methodology have emphasized event-related measurement, signifying more refined alignment of MRI-shadowed neuronal transactions with manipulated stimulus occurrences or task-trial types (e.g., Bandettini & Cox, 2000; Kourtzi & Kanawisher, 2001). To be sure, events of concern are not the stimulus occurrences or task trials themselves, but rather the cognitive or perceptual functions they are thought to evoke. Functions such as encoding stimulus probes with respect to spatial, affective, or other properties are deemed to have their own within-trial time course. Even the simple detection of stimulus onset comprises a complex dynamic process with a stochastic component (Smith, 1995).

The designated event in event-related fMRI evidently is a covert function or cognitive operation, whose tractability can be seen to depend on a valid formal model of task performance. If the model is dynamic and stochastic in nature, the time window of target-function presence can be estimated, with a stipulated envelope of error (statistical confidence level). In this way, times of measurement interest defensibly can complement brain regions of interest, to better calibrate space–time coordinates of fMRI assessment (Carter, Neufeld, & Benn, 1998; cf. Kosslyn, 1999).

Siegle, Steinhauer, Thase, Stenger, and Carter (2002) have used connectionist modeling to simulate the amygdala's fMRI signal response to processing of verbal affect by depressed and control individuals. The configuration of connectionist-model parameters tweaked to produce MRI-signal changes accompanying depressive symptomatology was then consulted in interpreting the algorithmic mechanisms of these changes (Marr, 1982).

Others have assessed MRI-monitored correspondence in activation of selected brain regions, expressing the regions' functional connectivity, during stimulus encoding (endowing presenting consonants with task-required lexical properties) performed by schizophrenic and control participants (Boksman et al., 2002). Stochastic modeling of task performance stands to augment such recordings by indicating key measurement epochs of MRI-monitored regional coactivation, according to modeled probabilities of target-function presence (Neufeld et al., 2002). Deviations in MRI measurements during the indicated epochs can then be imbued with functional significance, according to corresponding variation in parameter values of the modeled function. These values, moreover, are adaptable to individual participants through Bayesian estimation.

Advances in Model Construction, Refinement, and Testing

It is anticipated that continuing progress will be made in clinical cognitive science with respect to tests of cognitive model validity. An elegant example of evaluating competing models of decisional processes was presented by Busemeyer and Stout (2002). Stringent tests for model selection preceded application of the ascendent model to assessment of a specific debility. Three tenable models were compared for their efficacy in predicting and explaining performance of clinical and control participants on the Bechara Gambling Task (Bechara, Damasio, Tranel, & Damasio, 1997). Each model was tenable in that it expressed viable decision and choice mechanisms. The models were comparable, moreover, in their complexity (number of parameters invoked). The nature and organization of their respective sets of parameters nevertheless were distinct. The ascendent model therefore uniquely captured the workings of decisional processes evinced in task performance and thus imbued with greater meaning the values of its parameters, as estimated for the individual.

Methods of model selection and refinement, generally with clinical applicability, continue to progress (see, e.g., Myung, Forster, & Browne, 2000). Included, for instance, are techniques addressing a seemingly omnipresent construct in clinical cognitive science, that of automatic versus controlled or effortful processing (Shiffrin, 1988; see also Kahneman & Chajczyk, 1983). This construct has served to guide studies of maladies ranging from unipolar affective disorder to nicotine addiction (e.g., Baxter & Hinson, 2001; Hartlage, Alloy, Vázquez, & Dykman, 1993).

Key aspects of the above construct evince certain signatures in distributions of task-performance times (Townsend & Nozawa, 1995). These aspects comprise processing architecture, entailing (a) serial versus various parallel forms of handling task elements; (b) preservation of cognitive capacity, referring to mathematically indexed change in speed of processing with increased task load; and (c) stopping rules, meaning exhaustive treatment of stimulus elements, over and against self-termination after acquisition of sufficient information for responding. The presented diagnostics moreover exquisitely flow from their parent theoretical framework, a coveted ideal that sometimes seems to be the property of longer established sciences (Meehl, 1978). As a bonus, the techniques are robust, in that their validity, by and large, cuts across distributional specifics. This and related technology provably trump routinely promulgated methods that have been demonstrably outmoded for some two decades.

Concluding Comments

Performance models and affiliated paradigms from mainstream cognitive science have reinforced the technological armamentarium of clinical science and assessment. Clinical applications nevertheless may endow mainstream cognitive science with unique opportunities for model testing and modification. Models that parsimoniously capture performance deviations accompanying pathological conditions can be favored over those that are stretched or fail to capture such deviations.

Selected disorders conceivably inflict pathognomonic variations on normal cognition, which are alien to healthy states. Decisional anomalies attending disorders with documented neurology are one example (Busemeyer & Stout, 2002). Use of special populations can fortify the espoused interpretation of model features, according to their selective sensitivity to participants' diagnostic status, paralleling selective sensitivity to designated experimental manipulations. Compatible with this type of reciprocity is the mandate of a current U.S. National Institute of Mental Health initiative to promote translational research in behavioral sciences. The possible interchange between clinical and basic cognitive science seems reminiscent of developments in clinical neuropsychology, where tracking functions of neuroanatomical structures capitalized on behavioral changes attending clinical cases of brain lesion.

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