Nikos Green

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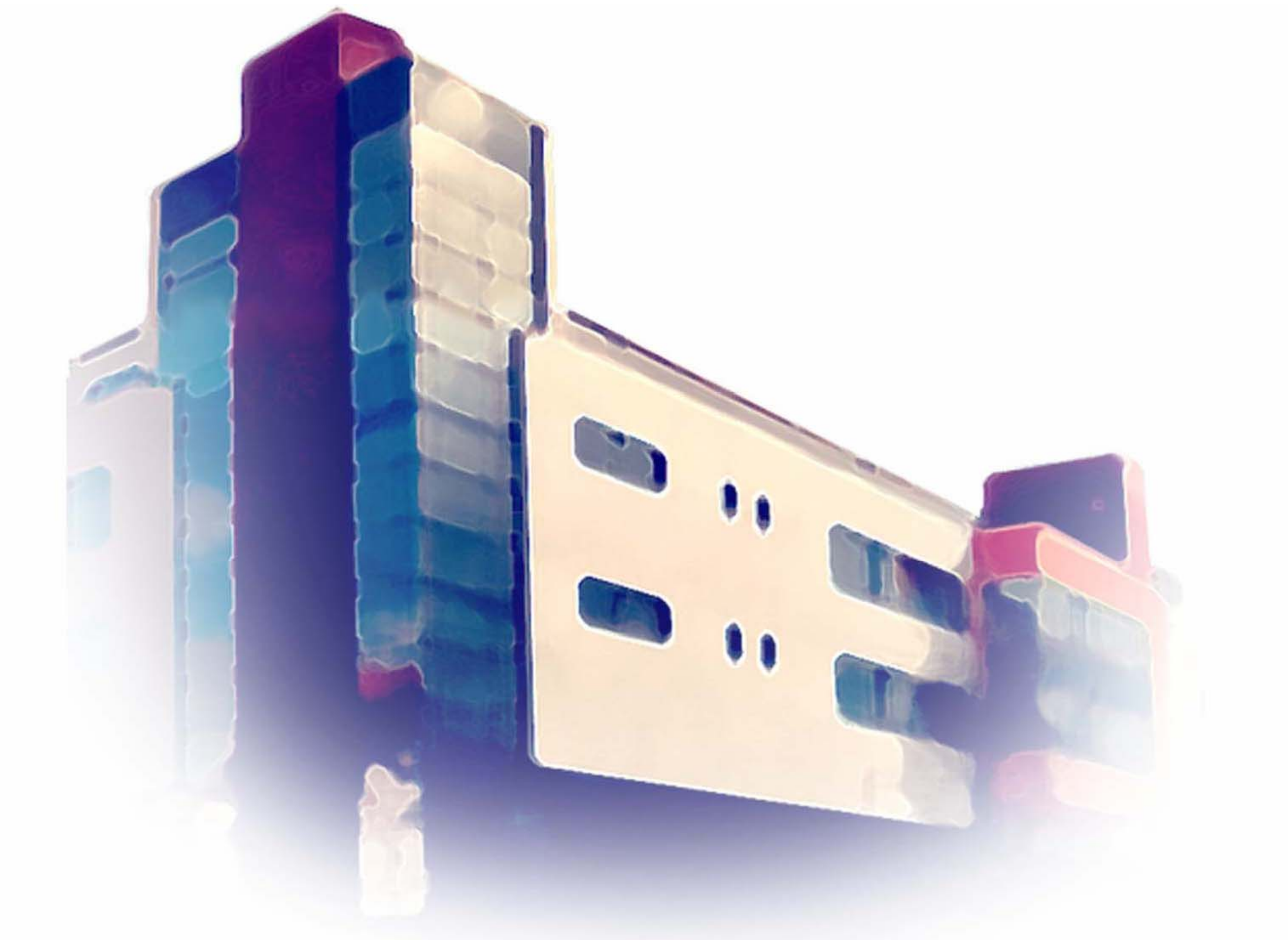
Motion influence on decision-making processes. A bounded relational approach within dynamic cognitive tuning frameworks



PICS

Publications of the Institute of Cognitive Science

Volume 1-2004

ISSN:	1610-5389
Series title:	PICS Publications of the Institute of Cognitive Science
Volume:	1-2004
Place of publication:	Osnabrück, Germany
Date:	September 2004
Editors:	Kai-Uwe Kühnberger Peter König Petra Ludewig
Cover design:	Thorsten Hinrichs

UNIVERSITÄT OSNABRÜCK

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Motion influence on decision-making processes.

A bounded rational approach within dynamic cognitive tuning frameworks.

Bachelor Thesis

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Spring 2004

In partial fulfilment of the requirements for a Bachelor of Science degree.

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Acknowledgements

The idea of writing this Bachelor thesis in the field of cognitive decision-making evolved during an internship at the Max-Planck-Institute in Berlin where I was introduced to the dynamical framework of cognition. I understand this framework as an excellent descriptive approach for complex cognitive processes. It integrates well into the interdisciplinary nature of cognitive science, since it addresses many aspects in ongoing discussions (for example the problem of mental representation). During my studies at the University of Osnabrueck there were no courses about this topic. It appears to be – as far as I can say – a good framework for approaching decision-making processes. Another reason that fascinated me is the possibility of developing a new model. If I am eligible to produce a scientific valuable contribution I would like to continue this research on various other levels (for example neuroscientific aspects) throughout graduate studies.

Especially, I would like to thank Dr. Jacqueline Griego and Dr. Markus Raab for their advice through a space of various new ideas. I also had the chance to do a main part on the thesis at the Indiana University Decision Research Lab. I thank Dr. Joe Johnson for very good comments and discussions about this work and for hosting me in Indiana. I would also like to thank Prof. Jerome Busemeyer for the possibility to work in his Decision Research Lab at Indiana University.

Abstract

MOVID (***MOV**ements **I**nfluence **D**ecisions*) is a (conceptual) dynamical model advancing a movement function-as-information framework. Grounded in the logic of Cognitive Tuning and Body Feedback theories this framework describes the influence of nonaffective internal motion signals on cognitive decision-making processes. It is formulated as a dynamical model adopting the decision-making principles of Decision Field Theory (DFT). So, MOVID is a dynamical decision-making model describing choice development of two distinct information processing modes on a (general) dual processing structure. With a bounded rational perspective this model accounts for situations of non-rational decision-making being contextually and cognitively focused on certain types of unconscious decision processes in uncertain environments. Bounded rationality refers to the best the decision maker can do facing these specific situations. The notion of bounded rationality highlights the importance of the structure of the contexts in which the behavior is observed. This work informs decision theories, such as Decision Field Theory (DFT), about the importance of the motor component as an input source (proposing the movement goal as information logic). Strictly speaking, MOVID is a model depicting the processes underlying unconscious cognitive decision mechanisms. It functions as a tool describing these decisions in specific environments . To test the proposed conceptual assumptions, the model is implemented into a DFT-based simulation environment in which it can be evaluated. It is validated by testing hypotheses that represent various contextual and cognitive settings in a MATLAB-based simulation environment.

Terms: *dynamical model, cognitive tuning, body feedback, DFT, bounded rationality, nonaffective information*

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1. INTRODUCTION

Human decision behaviour is highly sensitive to a wide variety of task and context factors. This work focuses especially on quick and unconscious decisions under the influence of internal signals (stemming) from the proprioceptive system. In MOVID an appropriate model is formulated that explains the importance of internal signals in decision-making processes. The context is restricted to the domains of internal proprioceptive information and unconscious decision making processes in uncertain environments (cf. Branscombe, 1988).

What is the functional role of the motor system when a decision is made? Normally, the answer would be that it executes and guides the choice related behavior constructed in higher level cognitive systems. However, there is more to this system (with focus on contexts of unconscious decision-making), specifically in fast environmental information extraction contexts. Leaving rational principles aside (cf. Shafir & LeBoeuf, 2002, Gigerenzer & Selten, 2001), taking an embodied situated dynamical approach (Port & van Gelder, 1995) the role of this system can be extended: it is information *providing*. Experiments showed (Raab & Green, in press) that arm movements of either approach or avoidance function provide positive or negative signals that influence task performance of participants under the influence of these signals. For example, in one experiment this internal information influenced (Raab & Green, in press) associate generation in a word association task. Positive signals trigged a creative generation mode whereas negative signals trigged systematic generation of associations.

Hence, MOVID inherits two categories of mechanisms: the modus operandi of information processing and an evaluation-adaptation mechanism in the decision process pointing out the important role of the motor system as information source. Both levels of processing (modus operandi and decision mechanism) interact dynamically.

Assuming these concepts, what kind of information flow is provided in our framework and how does this information influence decisions?

Approaching cognitive processes in cognitive science is important (Clark, 1987) and can be done through the modelling of the observed processes. The approach taken in decision-making models is descriptive (Strube, 1998, 2001) and is based on empirical observation and experimental studies of the process. Different modelling techniques can be used for the formulation and implementation of a model; in case of simulating and validating the MOVID model a dynamic-conceptual formulation and a probabilistic computational implementation (based on DFT) is used.

To be precise, MOVID depicts a restricted variety of decision situations; it describes choice (probability) development in types of situations that occur in a specific class of contextual and cognitive states. First, the environment in which a decision is made, is restricted to information that is available before semantic (conscious) environmental extraction. Second, the decision-making mechanism is described as fast (cf. Neumann & Strack, 2000) and dynamic. Hence, it precedes the semantic information extraction from the environment implying the evaluation of fast available (raw) information from the sensory (here proprioceptive) systems. Therefore, decision situations with the evaluative scope (appraising the personal current state of the decision maker) of attention on body feedback (like in fast information extraction situations) can be analysed with this model. Figure 1 shows the general idea of this work.

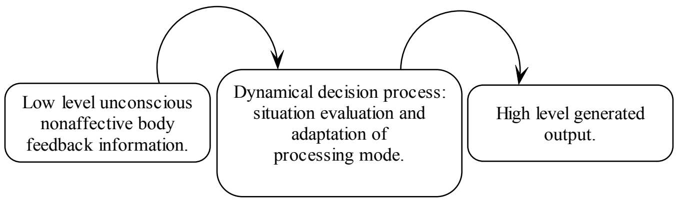

Figure 1. The general idea.

This decision-to-environment relation is assumed to be evolutionarily originated (cf. Watson, Wiese & Vaiyda, 1999; James, 1981; Darwin, 1870). Dynamical approaches along with situated and embodied principles can be used to explain cognition with emergent properties in the variety of unconscious and conscious information processing systems (Clark, 1997, 1999). Inherited in this framework is the idea that cognitive processes are influenced not only by conscious information evaluation (analytic process) but also by underlying unconscious signals (like proprioceptive signals). Decisions and related choice-preferences are heavily influenced by the nature and context of the decision mechanism and environment (Luce, 1964; Johnson & Raab, 2003). In this thesis work, an association task environment is used to exemplify these contexts. Participants under the influence of internal signals are supposed to generate associations for presented valenced words. MOVID explains how internal signals influence the decision about the modus operandi of information processing that is used to generate the association.

The process for generating an association, in the observed task where proprioceptive signals tune cognition, is based on choosing an option (processing mode related association) from a set of alternatives that reflect heuristic versus systematic modus operandi. Signals tune cognition in the sense that constraints of circumstance and adaptation are viewed as of outmost importance and are located; implying that context dependence is a central feature of all human endeavour.

So, it is not a purely rational mechanism; the agent is not fully aware of the construction of preference, rather these choices are made unconsciously. This is very important in terms of time and effort, as the construction of preference describes and explains the constraints on the interaction with the environment (embodied principles).

Choice probability in the construction of preference results from a decision-making (DM) mechanism that is described as fast and unconscious, basing on fast situation evaluation and non-analytic likelihood information process adaptation during deliberation phase. Thus, the choice probability reflects the modus operandi of information processing (heuristic or systematic).

The probabilities (formal: states in the preference space) of the two options are influenced by information provided by the environment (variables and initial conditions) and by the formulated decision mechanisms (interaction of the parameters). Cognitive parameters, for example attention focus, as well as lower level parameters, such as proprioceptive signals span the model's structure over different (interacting) levels of processing. It speaks for the reason to use this model as descriptive tool for unconscious decision-making contexts. The influence of internal signals can be experimentally designed by task set-ups that map to simulation settings. However, this is shown in the association task and will be part of the discussion section. The current section formulates the direction and aims of the work. The way to the model is made step-by-step.

Again, the grounding concepts are Cognitive Tuning- (Schwarz, 2002), Bodily Feedback- (Friedmann & Förster, 2002) and Decision Field Theory (Busemeyer, & Townsend, 1993) ideas. An interdisciplinary approach is taken in a model of decision-making incorporating the dynamical framework (cf. Chater 1998), computational cognitive models, and behavioral as well as psychological concepts (Anderson, 1996). Placing MOVID as a research work in the field of cognitive science relies on the fusion of various ideas from relevant fields.

The dual process structure of options justifies a task analysis for the association task in a way that allows modeling of the information processing mode as a binary choice in DFT. It is a large scale view which if taken to a micro analytic point of resolution can be modeled as a multivariate-option model based on existing DFT-applications (Roe, Busemeyer & Townsend, 2001). In such a model the choice variety can be extended by using more options, thus giving a fine grained analysis on different possible processing modes. This would also refer to the notion of the adaptive toolbox (Gigerenzer & Selten, 2001). Thereby a model can incorporate different choices for different types of situations, however the basic decision mechanism would stay the same. A deeper differentiation beyond binary choice (cf. Strack, 1999) increases the complexity and maybe approaches the cognitive reality more. Anyway, formulating MOVID with a dual process structure accounts for the general aspects of the observed decision contexts.

In examining decisions that are not analytic (at the end of a detailed, fully conscious and rational thinking process) the main point of this work will be to construct a model that describes the underlying mechanisms of fast decisions in uncertain environments. The mechanisms describe the parameter interactions.

Summing up, an interactive *dynamical model* that incorporates main aspects and concepts from the cognitive sciences is presented: Being a cognitive model it describes (within *situated cognition* logic) the influences of internal signals (originating in the proprioceptive system) onto higher order cognitive (decision) processes. The logic of MOVID is the 'movement as information idea' (see Raab & Green, in press).

Consequently, MOVID gives a greater insight into higher-order (decision) and lower-level (proprioceptive) component interaction. This idea is exposited by presenting slices of the basic concepts in the beginning with an explanation how there are linked to form the logic of this work. Afterwards the construction of MOVID will be made step-by-step leading to the implementation of the model. With the testing of the model assumptions in simulations, a validation will be made leading to the discussion section.

2. CONCEPTUAL SLICES

a. Internal Information

i.) Cognitive Tuning

The Cognitive Tuning (CT) framework (for an overview: Schwarz, 2002) is primarily presenting social cognitive aspects of behavioural tuning, proposing a rather wide range of influence sources such as moods, emotions and environmental cues. The core assumption within this logic (that is important for the model) is that the cognitive system uses spontaneously adopted reasoning styles to deal with the situation description provided by these cues.

Ottadi, Terkildsen and Hubbard (1997) show in their experiments that external valenced cues have an effect on cognitive processes (see Raab & Green for an overview) through nonaffective information provided by internal signals. In their experiment participants had to make verbal statements that were accompanied by videotaped persons producing happy, neutral or angry faces in a stereotyping paradigm. The results revealed that happy faces (external cues) elicit heuristically processed verbal statements whereas neutral and angry faces result in more systematically processed verbal statements.

Other external signals, like the background colour of the medium information is presented on serves also as cue (Sinclair, Soldat & Mark, 1997). In an experiment with this variable, participants performance on midterm examinations was influenced by the colour of the paper the questions were printed on. Schwarz (2002) presents this and other experimental results in his review.

According to CT these signals share one crucial characteristic: they provide cues that inform the agent about the nature of the situation and tune thereby cognitive processes. So the main suggestions of CT are:

1. *Cognitive processes are tuned to meet situational requirements.*
2. *These requirements arise via signals treatment from different (bodily-, environmental- and mood) domains.*

Cognitive tuning additionally suggests that positive affect focuses people on internal, subjective data, while negative affect focuses an agent on external, objective data, cuing (Schwarz, 2002) different processing modes.

Summing up, the general logic of CT suggests that cognition is tuned by different (qualitatively distinct) signals of internal and external origin through static adaptation mechanism(s). Thus the theory proposes a normative integration of the signals that is comparable to the hedonic state concept put forward by Friedman and Förster (2000). They claim that the signal is directly related to a hedonic state which triggers the further processing (mode) of information. This is a static mechanism, because it establishes a direct relation of the signal on the choice (signal→choice) without being able to adapt temporarily or change the choice.

However, MOVID avoids the idea of direct relation determination through hedonic states; it is rather argued for a functional complex dynamical mechanism that can adapt to temporary changes.

Of note, research in CT logic (with regard to internal signals) showed that there is no mood influence by internal motor signals (Soldat et al., 1997), which was also shown by Friedman and Foerster (2000) in their movement-position-as-influence framework. It is of importance because mood signals are excluded parameters in this model. Although mood signals can occur in the time frame of ms to seconds (as in affective priming that takes place in the 50 to 300ms range), they are excluded because functional signals of the proprioceptive system are independent of mood signals. An idea to integrate this effect later can be done through the threshold-parameter of our model (see MOVID section). CT frameworks have recently been linked to bodily sensations such as feedback signals from the proprioceptive system, showing the cueing of behavior by motor signals. These signals are conceptually bound together in the Body Feedback framework (Friedmann & Förster, 2000).

ii.) Body Feedback

What are these signals that are put forward and how can they be described?

Friedmann and Förster (2002) show in their experiments on Body Feedback (BF) influences that creative problem solving is enhanced when the agents arm is in a position which is, according to their framework, associated with approach reactions (flexing position the arm, as when pulling something toward oneself) than if it was in a position associated with avoidance reactions (arm extension position, as when pushing something away from oneself). Moreover, they claim that arm positions are associated with different hedonic states, representing a static situation evaluation of the arm position and of the information processing, because according to their ideas the position determines the quality of the signal and this signal determines the hedonic state and thus the modus operandi of information processing. Another example comes from Schwarz (2002), who presented internal arm position signals as cues that influence the performance on word completing tasks according to the above mentioned processing implications.

It is worth mentioning that in all experiments participants were unaware of any relation between the arm position and the attitudes that they formed about their stimuli, an argument underlining the unconscious operation mode of these signals. Mood has no effect, and there is no indirect influence of mood or attitudes on the processing mechanism. The current MOVID context excludes the triggering by mood effects the influences of aspects of cognitive capacity (such as attention) or cognitive evaluation and attitude formation. According to Chen & Chaiken (1999) processing mode one, termed the systematic processing mode, is a bottom-up mechanism with close attention to details. The opposite mechanism termed heuristic top-down mode, defined by less attention to the details at hand.

What we adopt from this framework is the following: Internal signals give qualitative feedback with no attitudinal or mood effect. However, the described static logic of mechanisms relation is not taken into account. Instead a dynamical mechanism is proposed.

b. Quality of Signals

Again, BF in a CT framework suggests that cognitive processing is cued by the present affective state that is elicited by motor signals, meaning that body feedback signals of benign (positive) or problematic (negative) quality trigger cognitive mechanisms (Schwarz, 2002; Friedman & Förster, 2000). In this view, positive bodily responses are typically associated with approach situations while negative bodily responses are associated with avoidance situations: positive affect signals that a situation is benign whereas negative affect indicates a dangerous situation.

A bodily response that is closely associated with approach (positive signal) is the contraction of the arm flexor, which is involved in pulling an object closer to the self. Conversely, contraction of the arm extensor is involved in pushing an object away from the self and is closely associated with avoidance (negative signal). Hence, arm flexion provides bodily feedback that is usually associated with approaching positive stimuli whereas arm extension provides bodily feedback that is usually associated with avoiding negative stimuli (see Cacioppo, Priester, & Berntson 1993).

Thus, the quality of BF signals depends on, or is related to, the arm movement function. These signals are not related to hedonic states in a static situation evaluation as claimed by Friedman and Foerster. Instead, they are merely integrated dynamically into a decision mechanism hereby triggering information processing modes. A proprioceptive information integration and emergent adaptation mechanism is proposed that allows for a non normative explanation of movement influences on higher order cognitive processes (such as decision-making). The important aspect of time can be taken into account, thereby modelling a real time interaction of human cognitive processing with the environment.

The movement functions as influence framework can now be constructed with the following aspects: First, in regard to the situated and bounded rational perspective on cognition, information processing is not only influenced by higher-order representational cognitive signals (such as word valence), but also by lower level signals from the motor system (such as arm movement function). A reference to movements of approach (arm flexion) and avoidance (arm extension) function is presented. Second, the movement functions submit distinct qualitative signals (problematic or benign; positive or negative) that relate to the nature of the current situation, thereby influencing the decision process over information processing modes. Thirdly, these mechanisms interact in time and are thus dynamically connected. These are unconscious processes of decision-making mechanisms integrating signals from the proprioceptive system into higher order cognitive systems.

The signals we focus on result from arm-movement functions. Negative signals, related to avoidance arm movement function (arm extension) generally mean that the situation is dangerous and require higher attention on the details at hand (related to a slow, detailed processing mode). On the contrary, positive signals that are related to approach arm movement functions (arm flexion) imply a benign situation characterization leading to a free exploration of the environment (related to a fast heuristic processing mode). For example, people move away physically through unconsciously elicited actions in response to situations where they are afraid or look away when feeling self-conscious, where the reasons are not consciously present.

Additionally we adapt the paradigm of DFT (Busemeyer & Townsend, 1992, 1993) that states: people try to approach situations that are characterized by a promise of positive or a lack of negative outcomes. Conversely they try to avoid situations that entail a threat or negative outcomes or a lack of positive ones. Under this premise, bodily responses influence the decision mechanism over different information processing styles depending on the context (the availability of information). The decision mechanism contains an evaluation of the internal signals (about the situation) and an adaptation for the best option (basing on the two processing modes) at this moment.

A situation evaluation is established in the decision mechanism leading to an emergent adaptation of the contextual circumstances. Adaptation to situational requirements is based on (choice as a simple dual-process model) distinct (dual) processing styles. So, the decision that is made relates to the best fitting operational processing mode. Thus, the decision mechanism leads to the most appropriate information processing mode under evaluation of the present situation.

Contexts are qualitatively evaluated dynamically, having processing implications that lie in the complexity of the decision process – guiding the preference of an option towards the most appropriate choice (related to the processing mode). Again, positive (approach) signals are cues that everything is fine and negative (avoidance) signals serve as problem representations. Therefore negative signals should lead to careful, detailed processing in the task, the systematic modus operandi. Positive signals should trigger heuristic (creative) processing modes toward the task requirements. For example in the association task the heuristic processing style should lead to a production of unknown new associations (enhancing creativity) whereas systematic processing should generate already known associations.

Important to note is the assumption that these signals are nonaffective. A direct influence path is assumed, excluding mood and related intermediate stages of pre-processing internal signals. Nonaffective information is based on signals consisting of elements of origin (modality, i.e. motor system stemming from evolutionary older perceptive - sense systems) and signal quality (describing the current situation).

This idea (Raab & Green, in press) is of special interest in decision situations that are task dependent (bounded) in the following way: a fast decision shall be made and thus information extracted from the environment is minimal, shifting the attention to available signals. These signals are preconscious, the decision maker is not aware of receiving the signals and cannot tell how a decision is made.

By assuming that this type of decision process is operating in unconscious processing modes, a rational construction of choice probability like in utility theory (Luce, Bush & Galantner, 1965) is avoided. The system is restricted to a model incorporating dynamical properties consisting of the following main elements:

1. Proprioceptive signal input,
2. dynamical integration and decision on binary processing alternatives,
3. choice for association word strength (emerging from processing mode).

c. Dual-process information processing model

Assuming two alternative processes with emphasis on nonaffective signals triggering the choice for one processing mode relates this work to dual process logic. The choice in the decision mechanism is made between two options (information processing modes) in a dual processing mode structure.

The main characteristics (Smith & DeCoster, 2000) of Dual Processing Models (DPM) are two different processing systems that are elicited under different circumstances (in our model by different adaptation mechanisms integrating the different signals). An appealing approach towards general dual processing models can be found in Sloman (1996). In his work he points out the possible necessity for a dual processing dichotomy of thought processes with regard to reasoning. He points out the complementary functionality of the systems that is needed by different kinds of tasks. Evans (2003) gives an overview of dual-processing accounts in the various areas of cognitive processes and emphasizes the distinction between two modes with different working implications based on preliminary work of Kahneman, Slovic and Tversky (1974). They formulate general assumptions for dual process models with the following distinction: a fast, cognitive undemanding system and a slow, cognitive demanding system. A general outline like this is adopted in MOVID, describing system 1(S1) as the faster and system 2 (S2) as the slower system. Note, that the model's time frame is set in the ms to sec band, a fast decision is therefore one in which the choice-probability is determined after for example 40 ms, a slower one say 120 ms.

Smith (2000) presents the general logic of dual-processing accounts for cognitive mechanisms as consisting of three structural elements:

1. two different processing modes,
2. their *interaction*,
3. *the circumstances* under which they are elicited.

Within MOVID, the tuning of the cognitive system (and thus the preference formation for one information processing mode) is established by a situation evaluation that leads to a situation adaptation. These mechanisms have emergent properties (implications) based on the parameter interactions of the dynamical model that operates on the dual process structure. The impact can be observed using an association task experiment.

Clearly, two processing systems S1 and S2 are proposed in order to explain and predict the results of the association task. Additionally (and more important) the arising information processing implications of the evaluation (deliberation) phase can be represented hereby: Input triggers evaluation, evaluation triggers adaptation, adaptation triggers process and process influences output (Figure 2). That means that the generated output is related to the processing mode in operation. This mode is related to the evaluation adaptation process and thereby linked to the signals. Entertaining the idea of a dual processing structure requires a clear characterization of these modes.

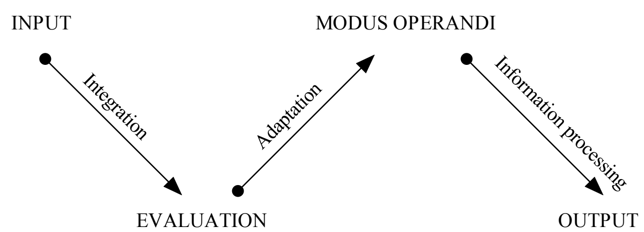

Figure 2. MOVID mechanisms.

i.) Processing modes

The afore mentioned idea of ‘best choice under the current situation evaluation’ requires the explanation of the two processing modes:

1. S1: A *heuristic information processing* system, enhancing free generation of association
2. S2: A *systematic information processing* system, restricting generation, relying on already generated knowledge

Our proposal assumes with regard to the ideas of cognitive stability and the least effort principle (Chen & Chaiken, 1999) that the heuristic processing mode (hp) is initially the default information processing mode used by human cognizers (however there are individual differences but they are not scope of this paper).

This entails two concurring processes: S1 (heuristic processing mode) is the default mode and S2 (the systematic processing mode) that can override S1 when the choice for it is dominant. The choice for S1 is triggered by positive internal signals whereas the choice for S2 is triggered by negative signals. Within the decision mechanism a context adaptation is made the following way: The cues (signals) influence the evaluation, the evaluation influences the modus operandi according to the principles of least effort and cognitive stability. Finally the modus operandi determines how the information is processed. For example, the process influences the kind of association generated.

In the first part of the model positive signals drive the choice for heuristic processing results or negative signals drive the choice for systematic processing results. Taking the sufficiency principle into account and referring to established dual processing models (Evans, 2003; Smith, 2000) it can be assumed that the heuristic information processing mode is used under positive input (positive situation evaluation) while negative signals (negative situation evaluation) trigger detailed, systematic processing.

Table 1 gives an overview of the characteristics of the processing modes.

Table 1. *Information processing modes.*

S2 (Systematic Processing)	*S1 (Heuristic Processing)*
Preferred under negative situation-evaluation	Preferred under positive situation-evaluation
Slower mechanism using detailed processing	Faster mechanism using heuristic processing
Switched-to mode	Default processing mode

ii.) Nonaffective cues and decisions

This dynamical framework contrasts the static (normative) approach of other works in describing the important development of the choice within a mechanism that evaluates signals and chooses based on probabilistic and dynamical paradigms between two processing modes. The evaluation is interesting because it links the cues with processing modes via the adaptation mechanism.

Actions (information) and the context in which we pursue them are represented at a greater level of detail when things go wrong then when things go well. It may be an unlikely action to take risks in a situation that is already marked as problematic. Here the best choice is to avoid simple heuristics and use a systematic way of information processing. When facing a benign situation that poses no particular problem, one may see little need to engage in detailed analyses relying on unusual routines and new knowledge structures, using heuristic information processing. This encourages additionally the idea that less effortful, heuristic top-down processing is the default information processing mode, unless evaluation and adaptation in the decision process trigger the change of modus operandi.

At this point, reflecting the mentioned ideas again seems appropriate. The idea that signals of the motor system trigger the information processing modes is grounded on two concepts. First, the signals influence the situation-evaluation (positive or negative) and second the situation adaptation that operates on a dual processing mode structure influences the preference development for the processing modes. This is the central evaluation adaptation mechanism of the decision process.

How the processing styles influence results depends on the characteristics of the task: Task performance is facilitated when the evoked style matches task requirements but impeded when it mismatches task requirements. This will be part of the MOVID section. In line with the conceptual ideas made earlier a basic element of the decision mechanism is presented next: Decision Field Theory (DFT).

c. Dynamical Decision Making: DFT

According to the purpose of this work - presenting and validating a model that incorporates a movement-functions as influence- it is required to incorporate the model in a dynamical decision framework. This framework should inherit features that can be used to model the conceptual assumptions. These features are found in DFT. Formally, they are represented as the system parameters such as bias, threshold and so forth. The adopted parameters in this model interact according to principled mathematical derivations specified by DFT (Busemeyer & Diederich, 2002).

Using the *Decision Field Theory* framework (Busemeyer & Townsend, 1993; Townsend & Busemeyer, 1995) enables the implementation of the contextual settings that are used in the model's theoretical structure. Taking this approach, it is possible to represent Body Feedback in a Cognitive Tuning Logic within a dynamical model of human cognitive decision processing. For this purpose MOVID will be implemented in a DFT-based MATLAB simulation environment (Johnson & Busemeyer, 2003).

DFT is a dynamical framework based on Markov processes in a sequential sampling mechanism that has been applied for a wide variety of modelling approaches towards human cognition, for example in conceptual categorization (Ashby, 2000; Nosofsky & Palmeri, 1995). DFT is based on research works on preferential choice (Aschenbrenner, Albert, & Schmalhofer, 1984).

i.) Core concepts of DFT

Some basic psychological assumptions of DFT are grounded in earlier work by Aschenbrenner et al. (1984). Their research concerning Cognitive Choice Processes and the Attitude-Behavior Relation tries to establish a predictive behavior framework in cognitive decision research for binary choices, showing further insights into the process that precede behavioural choice. Selectivity, flexibility and adaptivity principles are fusioned to form the Criterion-dependent-choice (CDC) model. CDC models postulate a sequential sampling process that results in an intention to choose one of two alternatives when enough evidence has been accumulated to be sure that this alternative is better than the other with respect to the situation and objectives. The same principles are essential to DFT.

One of the first steps in DFT is the integration of input by a sequential process. In the next step forming of preference states is performed according to the accumulated input information. CDC models claim that the sequence of processing depends on the importance of the dimensions with respect to the choice problem and thereby argue for context dependence. This idea points out that the aspect of information availability is regulated through the decision system by considering the importance of dimensions and the processing by importance of input. However, the evaluations depend on the context: they differ under distinct objectives, as for example in different tasks. CDC models also propose the sequential sampling integration of input, in which each preference state (evaluation at the current moment) is assumed to be added and compared to prior evaluations during the choice process, as it is done in the DFT deliberation process. These theoretical ideas are implemented in current DFT architectures as valence (integrated input) and preference (option contrasting choices in context).

Termination and choice in CDC models can also be found in DFT. CDC proposes that the threshold (they call it critical value) dependence on the situation evaluation and thus the context rather than on the choice-alternatives. In DFT we have the threshold that is adjusted to the circumstances, i.e. high for slow decision- and low for fast decision-contexts. Therefore the characteristics of sequential information processing and criterion dependent termination of the choice processes are basic assumptions of DFT (we also adapt these ideas in our model).

Aschenbrenner et al. (1984) additionally assume that stochastic choice models use heuristic rules that are applied to probabilistically selected information. Choices are based on sequential dimensional comparisons. The sequence of selecting dimensions for comparison is determined by the importance of the dimensions, analogous to the attention and weight values that are integrated in DFT models.

As said before, the underlying sequential sampling mechanism is used as a widely accepted modelling technique, it is also used to model other cognitive processes than decision-making, for example concept classification (Nosofsky & Palmeri, 1997). DFT predicts choice probabilities (reflecting the preference strength), as well as choice response times. These are important output values for testing and validating our model, because we can infer the processing mode by taking a backward explanation path in analysing them (see results section).

Note, that the MOVID model is implemented within DFT as a binary choice decision mechanism triggered by the input dimensions of proprioceptive information and other (here word valence) information. The model remains simple and explainable. However, it would be no problem to incorporate more dimensions (input sources). A multivariate option model can be used in such a case. There are DFT based applications that use a higher dimensionality (Diederich 1997; Johnson, & Busemeyer, 2003). In MOVID (next section) parameter formalizations are adapted from the DFT framework. They interact according to the afore mentioned ideas. They represent the movement function-as-information view very well. A detailed argumentation requires the enhancement of the level of resolution of the DFT framework at this point.

ii.) Decision-making in DFT

DFT (Busemeyer & Townsend, 1992, 1993) is a formal model defined in a dynamic-probabilistic framework (described by linear stochastic difference equations; see also Busemeyer & Townsend, 2000). The core assumption is a continuous cognitive processing, adopting a dynamical framework of the mind. Busemeyer and Townsend (1993) term DFT an “abstract representation” describing the “deliberation process” in which “computations are assumed to be realized by an underlying neural system”.

Accordingly, DFT generally assumes: if one makes a choice, the underlying mechanisms rely on the dynamic accumulation of noisy activation for each choice and the action whose activation (preference) first exceeds threshold is chosen. Basically, the evaluated input is integrated into preference states (reflecting the accumulated contrasting valence information for each choice option) showing the input-to-output relation. In the deliberation process the evaluation of consequences (outcome) of the available choices is made through valence contrasting. This is an important aspect for the MOVID model as it is the basic concept of the evaluation mechanism. In this mechanism the two option valences are contrasted to evaluate them at the current situation (current point of time).

The mechanism can be used to describe short (ms) as well as long (minutes to days) decision time frames. Deliberation (development of preference states) is a random walk process regulated by a threshold, with a boundary determining the choice probability of the different choices and the deliberation time for the choices. Again, the dynamic decision process is described formally by a Markov chain process (Diederich & Busemeyer, 2002) based on sequential sampling process ideas (DeGroot, 1970). Markov chain processes are stochastic processes giving the probability from one state to the next. The transition probability depends on the occurrence of one preceding event.

Decisions are based on the accumulation of the affective evaluations produced by each action until a threshold criterion is reached. At any moment in time, the decision maker is assumed to attend one of the possible input dimensions (modalities) leading to consequences for each action (related to preference state). However, attention fluctuates from moment to moment, for example to other input dimensions due to cognitive influences (capacity, availability of resources) or internal influences (internal signal transmission). Thus the attention can switch from t to t+1. The probability of attending to a particular dimension depends on the attention weight (setting). This parameter can model the importance of the input modalities (dimension) and thereby contexts in which (like in our model) motor input is highly relevant.

The input (formally stated in matrix form representing positive or negative stimuli of the modalities) serves as source for the valence construction of the available choices. It represents the anticipated value of an action at moment t. It is produced by the weighted sum of the input values connected to the choice. This is another important aspect since it enables the construction and formulation of the evaluation adaptation idea.

The valence of each action (input to output relation) is fed into a decision system that compares the valences and integrates these comparisons over time to produce a momentary preference state. Finally, this momentary preference state can be described by trajectory development for different options in the preference space showing the evolving decision process until a threshold is exceeded, at which point the decision is made. Figure 2 (Johnson & Busemeyer, 2003) represents the original DFT model.

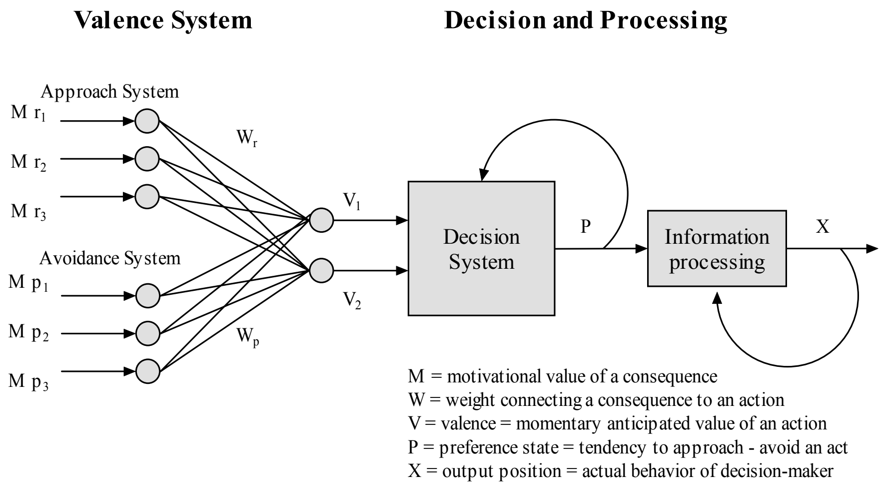

Figure 3. General Decision Field Theory model.

Summing up, a decision is reached by the following deliberation process: As attention switches from one event to another over time, different "affective" values are probabilistically selected and these values are compared across actions to produce valences. The valences are integrated into preferences for each action that are integrated over the deliberation steps to form preference states. The deliberation process continues until the trajectory for one action exceeds a threshold. It determines the choice probabilities and deliberation time of the choice. Technically, this is a Markov process based on matrix formulas that have been mathematically derived for computing the choice probabilities and the distribution of choice response times (see Busemeyer & Townsend, 1992; Busemeyer & Diederich, 2002; Johnson, & Busemeyer, 2003).

3. MOVID

The afore mentioned concepts are fusioned within MOVID, thereby forming a coherent explanation. It provides a model in which motor signals tune cognitive decision processes and on this path also cognitive information processing. MOVID addresses higher-level phenomena such as an adaptation effect (action selection and use) in the choice space and lower-level phenomena, such as the information of motor signals in cognitive decision processing. The evaluation process guides the adaptation of the processing mode (choice).

DFT based computational models enable simulations in a dynamic-probabilistic framework that have been applied to a variety of decision processes and tasks. The first step is the implementation of the model into the DFT framework, which is used for simulation. By setting parameters (e.g., bias, threshold; reflecting our conceptual assumptions) according to the contextual and conceptual (fast decisions in unknown environments) assumptions the following processing flow is constructed: Figure 4.

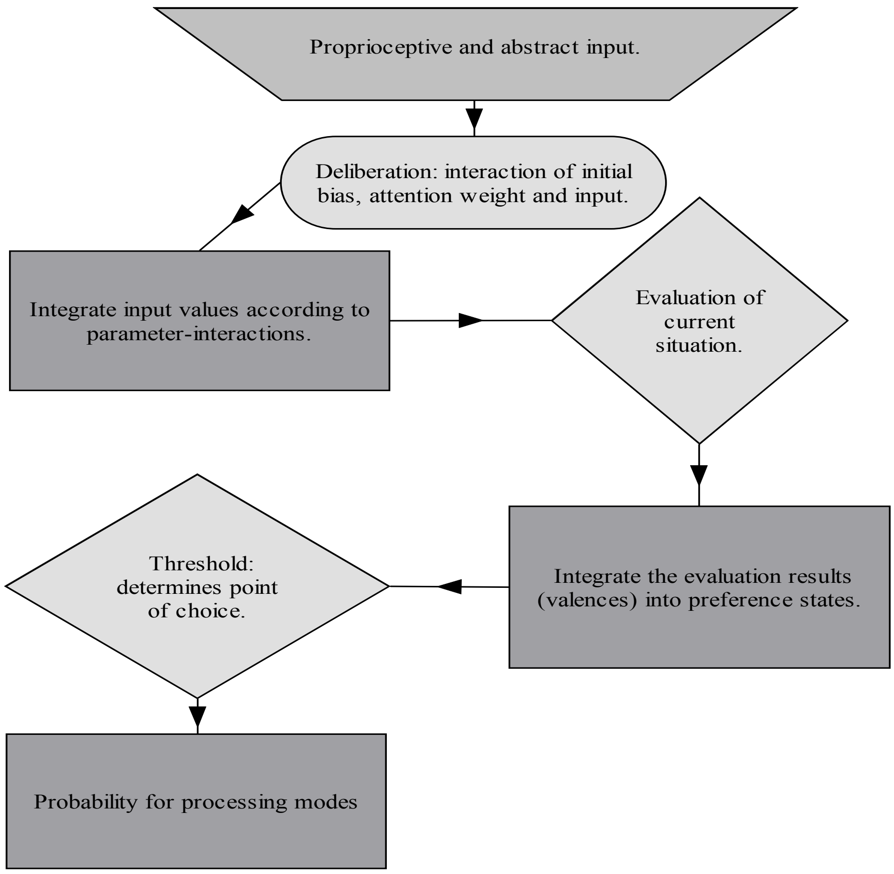

Figure 4. The processing flow within MOVID. Flowchart notation is used (see Appendix E).

The situation we take as exemplary context for this process is an association task in which the participant has to generate an associate for a presented (valenced) word. In this situation the participant (acting as decision maker) receives input via its visual system that is abstract (valence of the word) but also receives nonaffective motor signal information that additionally influences his unconscious decision over information-processing and thus the generation of an association. The action (generation of an association) reflects the processing mode taken in the following way: A heuristic processing mode leads to a free exploration of the environment therefore to a new ‘creative’ association whereas a systematic information processing mode focuses on already available knowledge, leading to a ‘known’ association generation.

Output (association results) is influenced by lower level motor signals and higher level cognitive signals of word valence and the mechanism parameters, attention probability, initial bias (preference for one of the two choices, representing default assumption) and threshold (conceptual: time amount available to the task; formal: time amount after which a decision is favoured to be reached).

The input signals represent (according to CT) cues that inform the participant about the situation nature and are formalized in the model as matrix entries. Other attributes are also used to represent various contextual settings for which decisions shall be described. First, attention probability is set according to the idea that the focus orients on situations with important proprioceptive input, because other information is not available (before semantic extraction of environmental signals). Secondly, the initial bias is set according to the assumption that one of the choice options is the default operational mode, thus accounting for cognitive stability principles. Finally, the threshold parameter represents situations in which fast decisions are made (due to task requirements).

The emergent situation adaptation within the cognitive decision process meeting the rising situational requirements (situation evaluation) under the influence of external (word valence) and the internal (movement function) information triggers the choice preference in an adaptive way. The signal valences/qualities are integrated and the best option according to the current contextual setting is chosen. This setting is formed on an evaluation of the signals: negative signals drive the preference for systematic processing, because this mode fits best to the implicated requirements of a negative situation. Adaptation is therefore the central aspect of this complex decision process. Most important are the evaluative mechanisms and the interaction of the parameters, they trigger the adaptation to construct the choice probability. This is the reason to label this mechanism emergent. It is a kind of systemic property of the overall decision-process on the general dual process structure.

Because of the qualitative categorizing of information the decision system can be seen partly as a response mechanism (S1 or S2) that adapts to the situation. Situations in which the bodily feedback has a high impact are constructed by cognitive as well as external influences. Generally it is assumed that decisions are made quickly, thus information about the situation depends mostly on the nonaffective information of motor signals.

To instantiate this idea, an evaluative adaptive mechanism is necessary in the decision system linking the internal information to processing modes. This mechanism is constructed with emergent properties of the model based on evaluation, thus forming preferences that trigger the adaptation (decision for one processing mode). This explanation is about the influence of lower level information on to the decision-making process. It will be explained as a backward reflection from the results (choice probability) to the mechanisms.

The effect of motor signal cues (positive or negative) on information processing tasks inform DFT about the importance of the motor component as well as cognitive science about basic processing styles of decision-making in certain situations. In MOVID the observed situation is an association task, yielding the following processes and results: The movement signals as well as the word valence strength trigger the preference for association strength in an indirect way by triggering the choice of the process that is used to generate the associated word (related to the processing style) and the reaction time for a choice under the binary choice logic. Therefore the model can be divided into following parts: The attribute triggers the evaluation, the evaluation triggers adaptation and adaptation predicts impact.

Structuring the information processing modes in a dichotomy keeps the model simple and uses a basic structure reflecting the two main different processing styles of human cognition. However, this general structure leaves the detailed exploration of the information processing modes to further research.

A bounded rational position is explicitly stated within this model. By integration of unconscious signals with probabilistic means (that result from interaction of internal and external domains) the ability to capture the adoption of different strategies and the environments they occur is given in MOVID.

Thus, the model is able to describe the interaction of cognitive environmental and internal cognitive domains. Using dynamical systems concepts allows for the mechanisms to be explained as an interaction of different cognitive levels within an emergent logic. The analogy can be drawn to a physical dynamical system: choice develops through the interaction from inside (DFT model) and perturbation from outside (input from the proprioceptive system). Controlled parameters within MOVID represent and model cognitive psychological assumptions. The coupling in the interaction of system components is a collective phenomenon of a nonlinear, recurrent dynamic of subsystems (valence, preference, integration, contrast). This macro structure view of cognitive decision processing, can be further sub modulated. That means that the used dual processing structure might be exchanged by a higher dimensional structure. Additionally the input dimensionality can be increased, accounting for more input sources than the ones stated in this work.

Summing up MOVID, the description of development, the emergence of new structures (here preferences) in the dynamical decision system is grounded in the parameter (inter)action and settings. The mathematical description through Markov processes (random walk) formulates the dynamical evolution of this decision process.

4. IMPLEMENTATION

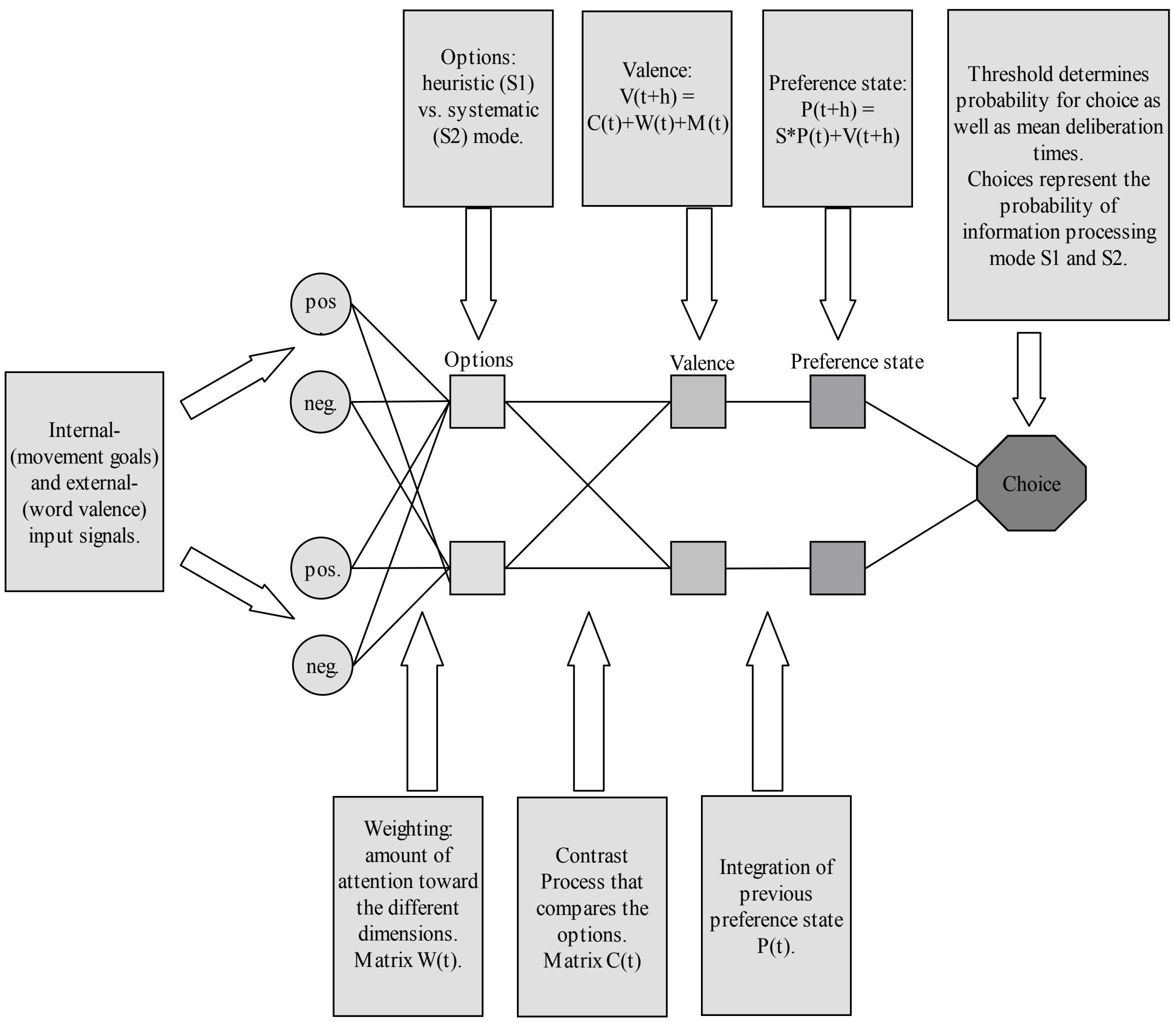

Figure 5. A DFT adapted MOVID model showing the different stages of processing in the decision mechanism.

Figure 5 shows the model implementation that be will described step by step.

A first important aspect to consider is found in the parameters and their interactions. For the implementation of MOVID into DFT the interesting parameters are: The staying probability, the feedback amount, the time step parameter, the threshold bound, the initial bias and the attention probability.

a. Parameters

As pointed out before, the parameters represent the underlying conceptual cognitive (dynamical hypothesis of cognition) and contextual (task boundaries such as fast decision situations) assumptions of the implemented MOVID model:

- The threshold value (conceptually) represents the amounts of detail spend on deliberating and thus influences the decision time (high threshold means longer deliberation times and thus more input integration). If the threshold is high the input has a higher influence on the outcome, because of the higher amount of input integration. The simulations will test low threshold effects vs. high threshold effects.
- Attention probability towards one dimension models the importance of the integrated modalities. The testing will cover cases in which the probability is high for attending the motor dimension. Obviously, this affects the outcome probability, for example in cases where the input of the motor signal is negative this should reduce the choice probability for S1, if for example the signal has a high negative influence it drives the preference for S2.
- The bias represents the initial preference for one choice option. By this it is possible to model the default processing mode idea in the model. Therefore, simulations will cover small vs. high preference in order to determine its amount of influence.

Input is represented and formally modeled as an input matrix, here with reference to the observed association task, the two modalities are proprioceptive signals and higher order word valence. These are formulated with discrete values (positive vs. negative) in order to keep the simulations simple. However, this modeling property can be changed to continuous values under successful model validation. Simulations will test negative versus positive input. This aspect is important to show the effects of qualitative distinct motion signal on preference development.

Table 2.*The model parameters.*

Variable / Properties	*Function*	*Concept*	*Influence*
Threshold (th)	Determines the point of decision.	Detail of deliberation.	Deliberation time and amount of input integration.
Initial bias (z)	Sets initial preference for choice.	Default processing mode (cognitive stability).	Drives the decision towards one option.
Attention weight (w)	Probabilities of attention on distinct input dimensions.	Represents contexts in which motor information is important.	Regulates dimensional importance.
Input matrix (M)	Input: signal quality.	Positive or negative signals.	Quality kind drives choice-probability.

The process begins at the input level that is formalized as a 2-dimensional quadratic matrix representing the (positive and negative) input of both distinct input modalities. Keeping the values binary, the input can be described in terms of M_1 (positive motor signal, negative word valence), or M_2 (negative motor input and positive word valence). This approach accounts for the simplifications in analysing the association task. Note, that in this task a word is presented while the participant performs one of the described arm movement functions. In the next step the deliberation process takes place (see Figure 3).
Formally this is the integration of the Contrast Matrix (represents the comparison of the available choices), the Input Matrix and the Weight Matrix (representing the attention on the dimensions).

The decision mechanism leads to (formalized in the formulas found in Diederich & Busemeyer 2002) a preference for one option or another by the following mechanism: Valences for each option are formed ($V(t) = CMW(t)$) by contrasting a given option's weight value with the other option's value (C-matrix). Additionally, input signals are integrated (M-matrix) and the attention weight lying on them (weights in W-matrix). The valences are integrated (sequentially sampled) forming preferences that are also integrated over time to form preference states. A preference state is formed out of the current valence to which the previous preference state is added: $P(t+1) = P(t) + V(t+1)$ (sequential sampling MARKOV process). When the threshold is reached choice probabilities (for both options) and response times are determined (see Figure 6).

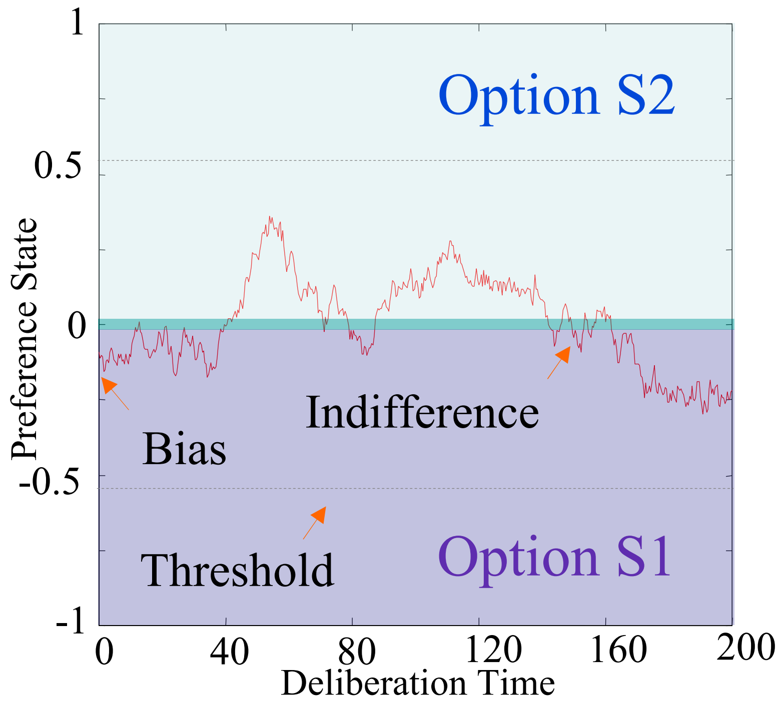

Figure 6. Developing decision process.

The mechanisms of accumulating input (through sequential sampling of proprioceptive signals) and integrating (by forming preference states) establish an (emergent) adaptation mechanism. Input and interaction drive the best fitting processing mode in the current situation.

b. Simulation

i.) Error estimation

To exclude errors such as result differences between various, distinct simulation runs, simulations with the same settings were made on four different machines using random parameter initialization in the same intervals. By obtaining 190 output units for every simulation enough results were given for a comparison. The results were compared one to one and they all matched 100%. This comparison shows that there are no differences to be expected in the outcomes under conditions of random parameter initialization. Obviously, the outcome depends on the simulation environment in MATLAB derived out of the formal equations (see APPENDIX B) of DFT.

ii.) Simulation

The DFT adapted MOVID environment simulates the afore-mentioned idea of internal motor signals as influence on decision-making. Our attention is focused on the empirical implementation part, the association task. Figure 7 gives an overview of the simulation process structure.

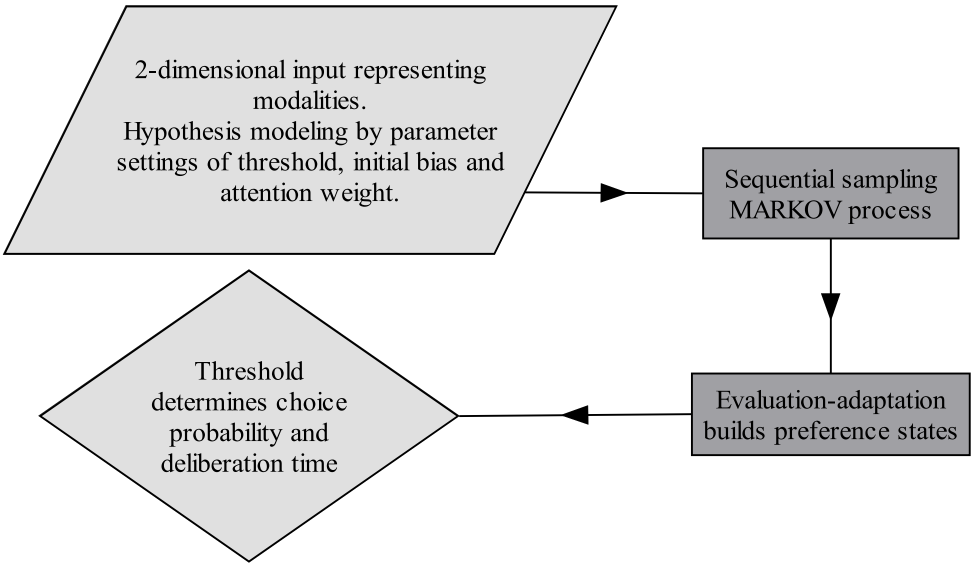

Figure 7. Simulation flow. The input and parameter interactions are the guiding elements of the integration process (sequential sampling) and preference state forming. The threshold determines the output (for notation, see Appendix E).

iii.) Assumptions

The parameters described in the previous section are used to represent the context that is described by the MOVID model: situations with high attention on sensorimotor input and fast decision environments. At first, assumptions are formulated according to the DFT adopted MOVID model. Hypotheses are constructed that can be simulated and validated. Parameter settings are mapped onto conceptual assumptions:

- The initial bias is set ($.1 < z < .9$) according to the assumption that heuristic information processing (S1) is the default mode. The lower bound represents a slight preference bias for S1 (moderate setting) and the upper bound represents a high biasing for S1 (high setting).
- The threshold is set (range: $1.2 <= th <= 2.1$) to test shorter vs. longer decisions. Note, that all thresholds model fast decisions (ms to sec time frame).
- Attention probability is higher ($p > .5$) on the dimension representing the proprioceptive input, because these are contexts that are in the modeling focus.
- Input is described by two cases, either positive motor and negative word valence input or negative motor and positive word valence input.

The above depicted settings allow for different conceptual assumptions:

Assumption 1: The higher the attention on dimension 2 (motor input), the higher the importance of the motor information.

Assumption 2: If the threshold is low the input of both modalities has a low influence on the choice probabilities (less information is integrated).

Assumption 3: Generally, the higher the initial bias the smaller the input and attention parameter impact on the outcome, but especially for negative motor input.

It is important to note that the simulations were conducted with a focus on the simulation environment (meaning the modeled situations): Of special interest is the construction of contexts grounded on parameter settings representing the general idea (see Figure 1). This leads to the modeling of contexts with important proprioceptive input (attention on that dimension is high), a small initial bias (input has a higher influence) and a high threshold (high amount of integrated input).

iv.) Hypotheses

According to the parameter interaction and settings, hypotheses are formulated (Table 3). Simulations of all parameter setting alternations were conducted, however a division into two subsets can be made: Set 1 contains all cases that have -according to our predictions- a dominant probability (>.5) for S1 (regardless of the input quality). Set 2 contains all cases that have - according to our assumptions - a dominant probability for S2 (under negative signal transmission).

With focus on the association task and following Friedmann's and Förster's (2000) creativity argument, that states creativity is enhanced under heuristic information processing and Hager's word association evaluation (1994), that describes the relative relation of generated and associated word by valence values, first general predictions are: in cases of dominant S1 probability, the generated word is of positive valence whereas in cases of a dominant S2 probability the word is of negative valence.

Table 3 represents different parameter settings and thus the tested task situations:

Table 3. *Simulation sets; h = high, l = low, p = positive, n = negative. The shown parameter settings are used to model hypothesis in the MATLAB based MOVID simulation.*

Variable / Cases	*1.*	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*	*11.*	*12.*	*13.*	*14.*	*15.*	*16.*
Threshold	h	h	l	l	h	h	h	h	l	l	l	l	h	h	l	l
Initial bias on S1	h	h	h	h	l	l	h	h	h	h	l	l	l	l	l	l
Attention weight	h	h	h	h	h	h	l	l	l	l	l	l	l	l	h	h
Proprioceptive input	p	n	p	n	p	n	p	n	p	n	p	n	p	n	p	n

Set 1 contains cases 1 to 5 and 7 to 16. For example, case 1 presents a situation with positive input with a high threshold (many steps of integration), a high attention on the motor dimension (the input is weighted heavily) and a high initial preference for the default mode (choice under positive evaluation is biased). According to our assumptions these cases should have a dominant probability for S1.

In contrast, case 6 and 14 form set 2. Case 6 is a context with negative input, a high threshold and a high attention weight but a low initial preference. With regard to the assumptions this case should have a dominant probability for the switched-to mode (S2).

Before coming to the results I will explain the modeling of the different cases in the implementation with numerical values: The threshold is set in an interval ranging from 1.2 to 2 with .1 steps, where 1.2 is the lower bound and 2 the upper bound. The initial bias is set from .1 (lower bound) to .9 (upper bound) with .1 steps and the attention weight on the first dimension (note that dimension 1 and dimension 2 attention values complete to 1) is set in an interval from .9 (upper bound)) to .5 (lower bound) with .1 steps.

5. RESULTS

Data (simulation output) was analyzed in independent t-tests with the probability of the S1 mode (note that probabilities of choices are complementary, p(S2) = 1- p(S1)) as the dependent variable and the input (negative vs. positive signal) as the grouping variable. Comparing specifically the means of the choice probability collapsing over the free variables is one way of analyzing the parameters. The hypothesis is: If the parameters are set as in case 6 and 16 (low bias, high threshold, high attention or low bias, low threshold and high attention respectively) and the input is negative there is a switch from the default processing mode S1 (heuristic) to the alternative option S2 (systematic). Both cases represent especially contexts that shall be described and explained by MOVID. Therein, attention on input is high and preference is biased only to a small degree.

Altogether eight t-tests were conducted (compare the means between 16 input groups). This multiple testing of hypothesis requires attention to the Type I error rate, because the tests were run on the same data collection. Bonferoni correction covered this aspect and controlled for inflation of alpha.

Table 4 lists the tests that were run on the data. The notation is analogous to the parameter terminology. Threshold is the critical value representing the point a decision is made, bias is the initial bias and att_weight is the attention weight on the motor input dimension. The following tests were conducted (cases refer to Table 3). Note that the grouping variable is the input quality (positive or negative motor input), the dependent variable is the choice probability (for the default processing mode S1) and the independent variables are the case settings of the bias, the threshold and the attention weight.

Table 4. *T-test settings.*

1.	First t test, cases 1 and 2:	threshold >=1.8 & bias >=.7 & att_weight >=.7.
2.	Second t test, cases 7 and 8:	threshold >=1.8 & bias >=.7 & att_weight <=.6.
3.	Third t test cases, 13 and 14:	threshold >=1.8 & bias <=.3 & att_weight <=.6.
4.	Fourth t test, cases 5 and 6:	threshold >=1.8 & bias <=.3 & att_weight >=.7.
5.	Fifth t test, cases 3 and 4:	threshold <=1.4 & bias >=.7 & att_weight >=.7.
6.	Sixth t test, cases 9 and 10:	threshold <=1.4 & bias >=.7 & att_weight <=.6.
7.	Seventh t test, cases 11 and 12:	threshold <=1.4 & bias <=.3 & att_weight <=.6.
8.	Eighth t test, cases 15 and 16:	threshold <=1.4 & bias <=.3 & att_weight >=.7.

Presenting all results would lead to confusion because of data amount. According to the assumptions only the most important results will be presented, that is the cases that model the contexts that are of special interest. Importance relates to parameter settings that tested the conceptual assumptions of the task context modeling (see Appendix D for the remaining tests). Specifically, the results for important contexts (high attention on motor input) are presented. Emphasizing test 4 and 8 will lay the basis for the discussion because they represent situations that shall be explained by the MOVID model.

First of all some general results will be presented to overview the outcome and analyze each variable's influence. To prevent confusion following notation is used: M_{xy} is the mean with x being the test number and y the group number that refers to qualitative distinct input (1 = positive input, 2 = negative input); for example M_{41} refers to t-test 4 and the positive input group.

Nearly all tests show a significant difference between mean choice probabilities. Another important observation is that *p* stays under or equal to .001, meaning that there is no inflation of alpha. Considering the aim of this work and the above statement, the important tests are 1, 4 and 8. In case 1 all parameter settings are high. Test 4 and 8 analyze settings that representing conceptual assumptions about the contexts MOVID is developed for.

In the context of test 4 defined in case 6, the mean probability of the default heuristic processing with negative input (M_{42} = .43, SD_{42} = .063) is significantly lower than with positive motor input of case 5 (M_{41} =.75 SD_{41} = .05), t (27) = 20,384, p < .001.

In the context of test 1 cases 1 and 2 show also a significant difference in mean probabilities: M_{11} = .95, SD_{11} = .025 and M_{12} = .82, SD_{12} = .07. t(27) = 8.7 , sig. < .001. However the probabilities for S1 always remain dominant (bias is set high).

In the context of test 8 cases 15 and 16, the mean probabilities are significantly different according to input quality (M_{81} = .70, SD_{81} = .05 whereas M_{82} =.48 and SD_{82} = .06), t (27) = 14,303, p < .001. A switching of default (heuristic) to systematic processing mode is observable since the mean probability for S2 (1-p(S1)) = .52 is dominant.

Important to mention is that only tests 4 and 8 show a mean probability for the systematic processing mode under negative input influence. It can be assumed that the parameters have different impact on the choice probability.

The next graphs reveal the parameter influences in more detail. They provide a better understanding of the influence of each parameter on choice probability.

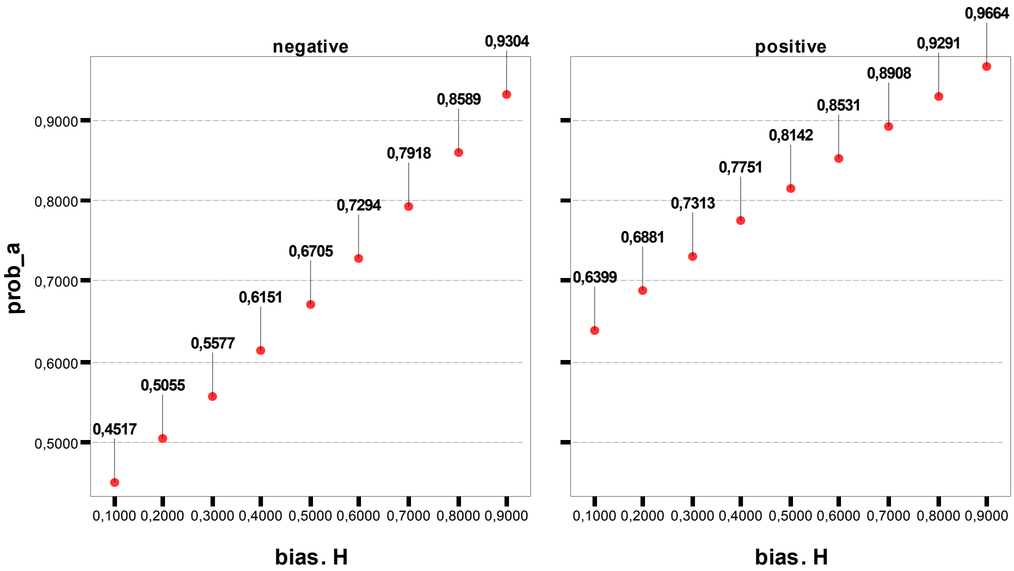

Figure 8. Parameter interaction: Choice probability S1 – initial bias interaction. Dots show means – left side negative motor input (positive word valence input), right side positive motor input (negative word valence input).

Figure 8 shows the impact of bias parameter on probability development: The higher the bias the higher the probability of S1-choice. The bias seems to correlate highly with the choice probability. With a small bias and negative input S2 (see left diagram) can have a dominant probability as it can be seen in the left diagram where p (S2) >.5 (bias = .1). It reveals that the preference and the resulting probability are influenced heavily by the strength of the bias in fast unconscious decision contexts. Only with small bias there is a switch to the alternative processing mode observable.

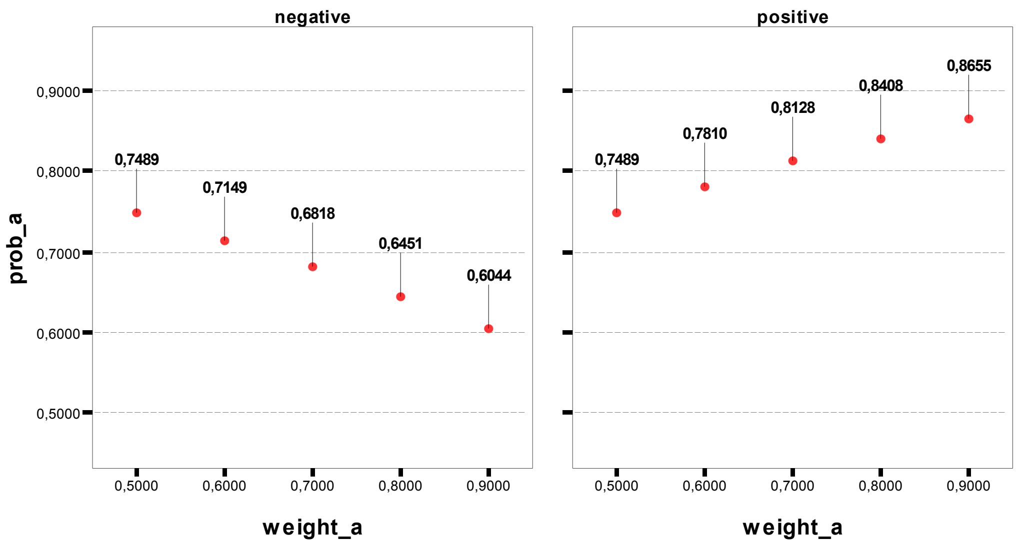

Figure 9. Parameter interaction: Choice probability S1 - attention weight interaction. Dots show means – left side negative motor input (positive word valence input), right side positive motor input (negative word valence input).

Figure 9 shows the attention weight guiding the input influence on probability means: the higher the weight the more influence on preference development through the input (quality). This can be inferred from the slopes when connecting the points: on the left diagram it can be seen that negative input drives the probability towards S2. However, note that in neither of the two graphs the S1 probability sinks below the dominant value. Thus attention weight is less influential on probability than the bias parameter. This also reveals the idea that in fast decisions the amount of signal integration is overall minimal. The attention parameter impact can be described as having a ‘guiding’ role.

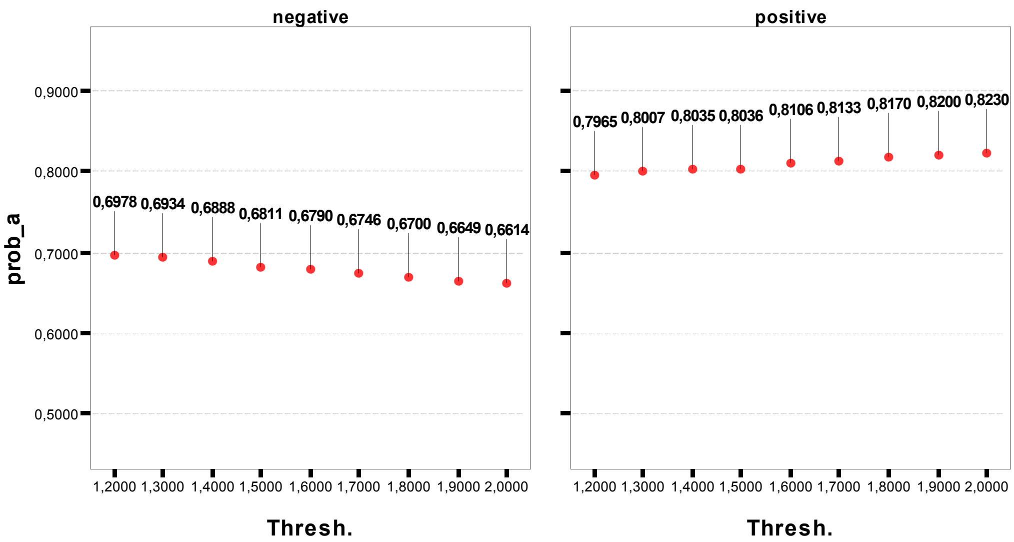

Figure 10. Parameter interaction: Choice probability S1 – threshold interaction. Dots show means – left side negative motor input (positive word valence input), right side positive motor input (negative word valence input).

A high threshold means more input integration because the deliberation phase is longer. However, the parameter impacts the probability only to a small degree. It can be observed that it has the smallest variance of probability, the region of S1 choice probability lays in an interval of .70 to .66 (for negative input) and .80 to .82 (for positive input). However, a guiding influence of input can be observed, as the probability development is dependent on the input quality: threshold and negative input develop on a downward slope (probability for S1 decreases with threshold increase) whereas increasing threshold and positive input develop an upward slope (probability for S1 increases with threshold increase).

Another way of looking at the parameters is their interaction. In the following passage I will present parameter pairs collapsing over the probability. Other kinds of understanding emerge, specifically important in arguing for the case construction in Table 3 of the simulation section. Context modeling will become clearer, because the parameters are used to model specific situations.

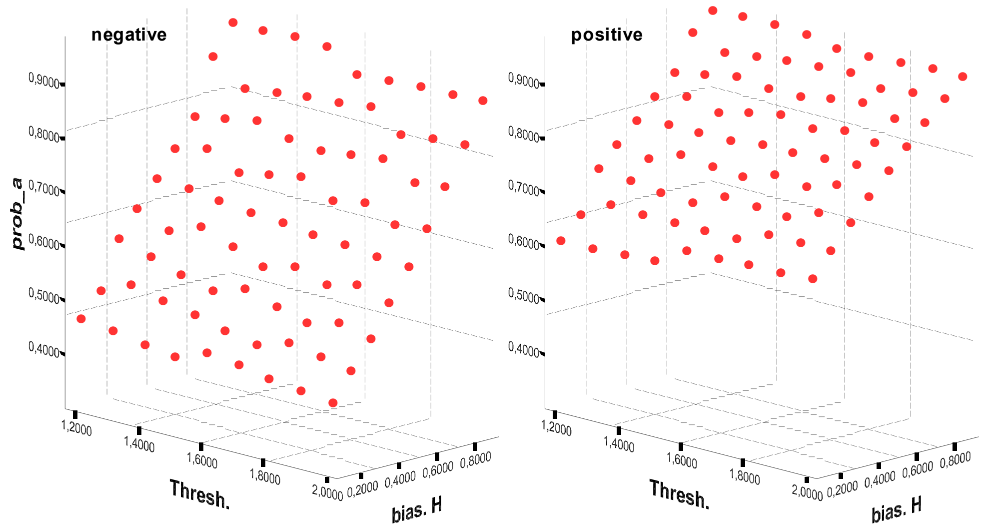

Figure 11. Bias and threshold collapsing over choice probability of S1.

In this diagram one can see that the interaction of threshold and bias works according to the assumptions. For example in the left graph on the top left corner we see the highest probability with low threshold and high bias. This shows that less information is integrated when the preference is heavily biased. As the threshold rises, more input is integrated and thus the bias for preference becomes less influential (top right corner). However, bias has a higher overall impact on the choice probability.

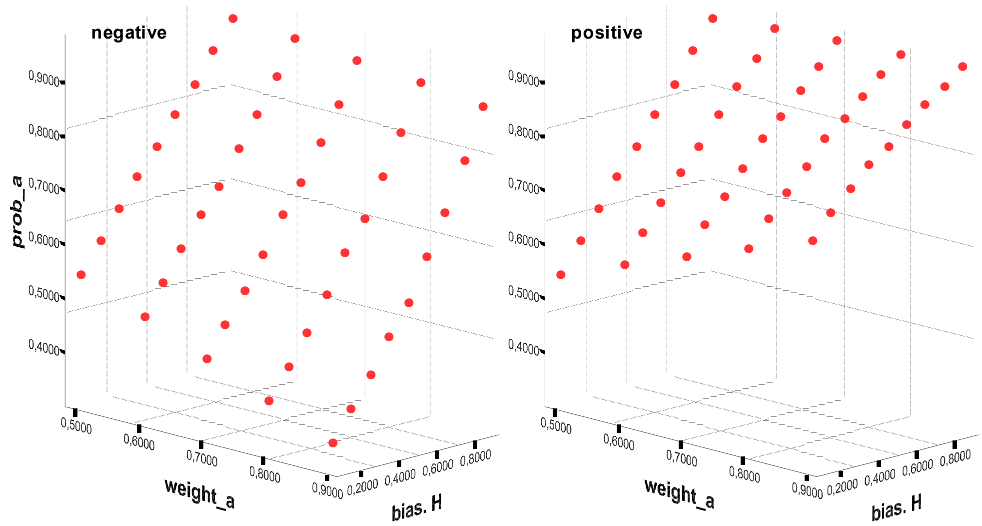

Figure 12. Attention weight and bias collapsing over choice probability of S1.

In these graphs the same inference can be drawn as in the above case. The higher the attention weights the more impact by the input. Bias has a higher influence than the attention weight. For example situations can be imagined with a high focus on motor input; however, because this context is known, the bias for a processing mode is high thus making the signal input redundant.

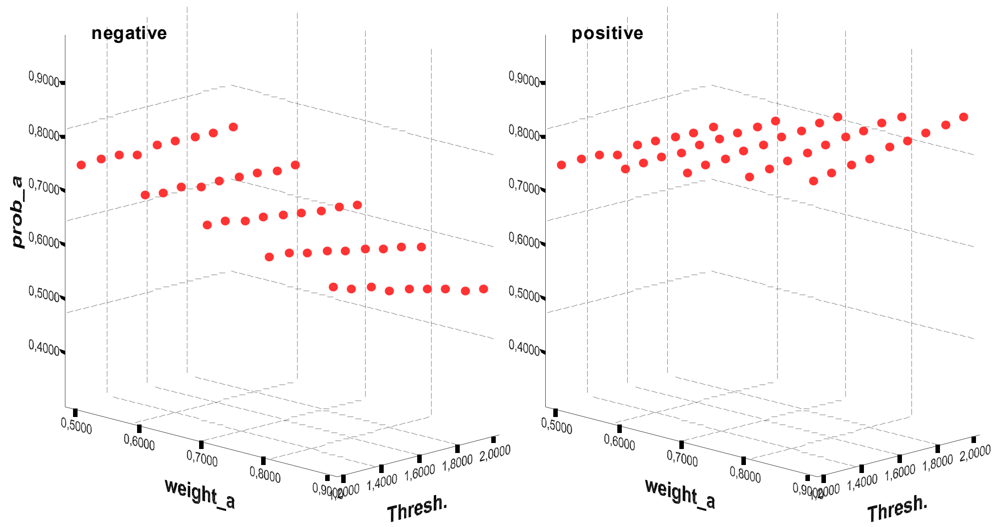

Figure 13. Attention weight and threshold collapsing over choice probability of S1.

Observable is a minor influence by the weight and threshold parameters. They show a narrow range of choice probability change. The change lies in an interval between .6 - .8 for negative input and .7 - .9 for positive input. This reveals the fact that in fast decision contexts the threshold parameter and attention weight function can be seen as a directing function. Their role is seen in the following interaction: The higher their value, the higher the input integration and impact (negative input has a downward slope reflecting the choice probability development towards S2 and positive input shows an upward slope reflecting the choice probability development towards S1).

Another aspect when analyzing the results is the prediction in the word association task: What might these predictions imply if this was the word association task with arm movements? This question remains for the discussion.

6. DISCUSSION

a. General Discussion

MOVID is a dynamic probabilistic model describing the influence of proprioceptive signals in decision-making processes. The central mechanism is an evaluation-adaptation process that is based on the ideas of Cognitive Tuning, Body Feedback and Decision Field Theory frameworks. Information flow within this model is based on sequential-sampling Markov processes that are the building blocks of DFT. Because MOVID describes fast unconscious decisions in uncertain environments, the simulation made use of hypothetical contexts, which represent fast, unconscious decisions in uncertain environments.

Therefore, various parameter settings (of input quality, bias, threshold and attention weight) have been constructed for the simulations.

From a descriptive point, the results indicate a parameter impact order: bias has the highest influence on preference development (represents the likeliness of a choice) followed by attention weight. The threshold parameter has the lowest influence on the choice. On a formal level this is due to the defined parameter interactions. Conceptually, in contexts where a fast decision is made it is obviously the case that bias has the highest impact because less external and internal information is integrated. The preference formation is highly influenced by the bias value and to a smaller amount by the signal values.

This reveals the difference of cognitive aspects in the decision context. So, with a high bias the uncertainty of environment is small, because the decision system might recognize a certain type of situation that is known. For this there might exist a strategy of behaviour, leading to a biased decision in which the integration of available information (as proprioceptive information) is reduced. In the opposite case, if the bias is low the uncertainty is high, because the situation that has to be dealt with is unknown. In such a context, the decision system integrates more of the available information, for example from the motor system. This information thus triggers the choice via the evaluation adaptation mechanism.

With regard to these conceptual assumptions following statements can be derived from the simulation results: In fast decisions the internal (motor) information has an increasing impact when the decision is not highly biased (bias <=.3) and if a high attention weight (>=.7) lies on the internal dimension of the proprioceptive input. It is to mention that a small bias is set in every context set up because of cognitive stability. By this the preference for the heuristic processing mode, the default processing mode, is given and represents the assumption that the cognitive system operates continuously in one mode and switches to other modes if needs arise in the current situation.

However, the bias can itself be related to the choice outcome, in a feedback mechanism (see next section) that might explain training effects.

Cognitive process modelling is based upon modelling contexts that have been or will be experimentally applied. One experimental situation in which internal motor signal influence decisions is the afore mentioned word association task. In this task the participant has to generate an association to a word that is presented while he performs arm movements. With regard to the above statements, the influence of these signals is significant in contexts that are modelled with a low bias, a high attention on the proprioceptive input dimension, uncertain environments (unknown words) and a threshold at the upper bound on the fast decision interval. Note, that fast decision contexts are observed, so although the threshold is set on the upper bound it still models short deliberation processes. Obviously, this implies a weak impact on the choice probability, because in a short deliberation, few input signals are integrated. Keep in mind, that the choice probability relies on the interaction of these parameters settings.

The results of the simulation validate this assumption. The dominant probability changes in accordance to the input quality. Thus negative signals trigger the preference state for the systematic mode and are correlated to the choice of option S2, whereas it is the other way round for positive signals. For the word association task this implies different outcomes. The generated association is influenced by the processing mode. A dominant probability for systematic processing leads to a generation of already known associations because the word presented is processed in a systematic way. In contrast, under the use of the heuristic processing mode an unknown association is generated.

Yet this first distinction is rough. It is assumed that the generation and valence of the association is related to the choice probability of the processing mode (cf. Bagozzi, Dholakia & Basuroy, 2003). No exact statements can be made here. A possible relation can be established between the strength of valence of the presented and generated word. The concept of valence at this point is not related to the valence concept in the model implementation. It rather represents the relative relation strength between the presented word and the associated word. This idea bases on the Hager word norm list for German words (1994) and has to be understood the following way: A high valence value in the association task describes a near relation of presented and generated word, whereas a low valence value describes a wide relation.

Therefore, according to the definition of the processing modes, in systematic processing the valence value is higher than that in cases of heuristic processing. In systematic processing (negative evaluation of the situation), the focus of the mechanism for generation of an association is based on already known associations, whereas in heuristic processing (benign situation evaluation) the focus is not constrained and an exploration of the association space is likely (representing creativity).

Other task set-ups can additionally be considered. For example, boundaries can be used in the task. Time-pressure is one constraint that can be used to further explore the decision context. This can be modelled by the threshold parameter. In such a case the parameter impact would change, because due to time limitations the integration of input will be reduced. The attention focus can be manipulated by coupling the arm movement function to a visual stimulus. For example, in the task the arm movement function could be visually manifested through a moving object while the participant has to perform on a cognitive task. This can be formalized by an additional input dimension. The bias of the task can be manipulated by the structure of the task, for example if the presented stimuli occur more than once. In such a case uncertainty will be reduced.

MOVID can be extended to capture these different hypothetical task set-ups. As it is validated through the simulation results and exemplified in the light of the association task, this first model is a very good basis for research in decision-making of unconscious processing in uncertain environments. From this basis there are different directions to continue investigations, such as the increase of the model's complexity (section c) or the mapping to other domains (section b) of explanation.

b. Feedback mechanism

One such extension of the model is a habit forming reinforcement feedback mechanism. The idea is a proportional amount of feedback related to the choice probability of the dominant choice on the initial preference (bias). This mechanism could describe the effects of previous choices on future behavior thereby introducing a training effect that leads to habitual behavior (cf. Werth, Strack, & Förster, 2002).

The equation $z(t+1) = (Pr(S1) - .5) \cdot th/k$ (1), where k is a constant factor depending on the threshold scale, z the initial bias and Pr(x) the choice probability of the previous dominant choice, represents the formal idea of this mechanism. Equation 1 can be described as follows: After a decision is made, the current choice influences future preference for a certain option because feedback information is integrated into the bias of preference states.

For example a choice for heuristic processing enhances the bias for the default mode whereas the choice for systematic processing reduces it.

Anyway, this idea is further ahead as it is dealing with a variety of other concepts (i.e. habit forming, training effects) that can be discussed in detail in future research.

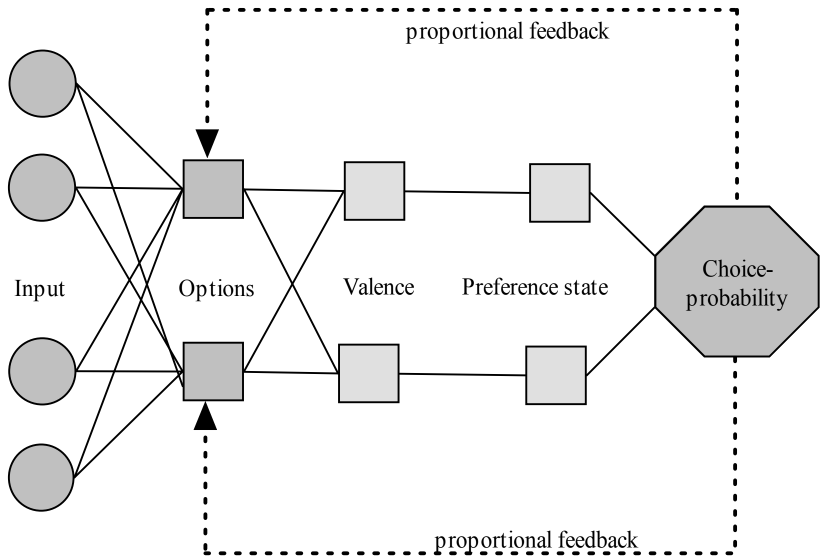

Figure 14. The feedback mechanism.

c. Long range outlook: Neuroscientific approaches to decision-making

An interesting aspect is the variety of neuroscientific approaches to decision-making (e.g. Platt, 2002) that try to match the domains of higher order cognitive processes to their neural correlates. Of interest with regard to these approaches would be to study the sensorimotor system under a neurobiological perspective and examine the origins of approach and avoidance signals we presented in this work. Recent fMRI studies reveal that neural correlates of proprioceptive information about one's own movements can be found (Leube et al., in press). Thus, it can be assumed that there are neurons or spike patterns in neural firing that code feedback information revealing that the sensory system gives relevant contextual information that is integrated into higher level cognitive processing.

Moreover, neuroscientific approaches can be of significant contribution to the dynamical hypothesis of cognition. Dynamics in neuronal processes could be tied with dynamical modelling approaches yielding a stronger explanatory framework.

d. Concluding Comments

The complexity of human cognition (e.g., the process of decision-making) must be approached by taking into account also non rational aspects of cognition, a cognitive perspective (Busemeyer, Hastie & Medin, 1995). These non rational aspects can be formulated as limitations in the resources one has in real decision-making environments: limited time, incomplete information and constrained computational ability.

To a great extent these aspects are found in unconscious cognitive processes that can be described best with dynamical means. By combining this approach with the notion of bounded rationality and the ideas of embodied and situated nature of cognition, complex cognitive processes can be described more adequately. Starting with simple models and increasing the complexity after validating the first assumptions might lead to an explanatory framework with great descriptive power that can be implemented into the concept of the adaptive toolbox (Gigerenzer & Todd, 1999). Because MOVID is validated by the results as a descriptive model, it extends the general DFT framework that was applied in the last decade to various tasks such as gambling tasks or trial tasks. It thereby informs DFT about the importance of the motor component as part of the decision-making mechanism and in which situations this influence might be relevant. I link it to the notion of the adaptive toolbox. This is a concept used in the bounded rational framework. The toolbox can be understood as a set of different tools that are used in different decision contexts. The use of certain kind of tool is related to the ecological nature of rationality; due to different cognitive, as well as environmental limitations, a decision making process is not a purely rational computation but rather a probabilistic mechanism. MOVID is a tool for a specific kind of cognitive and environmental context, thus it can be linked in future applications to the adaptive toolbox as a tool for fast decisions in uncertain environments.

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8. APPENDIX

A. Formal aspects of DFT (adapted from Johnson, & Busemeyer, 2003)

The dynamical system used to generate this deliberation process is presented next, and the connectionist network is represented in the next figure. The two choices corresponding to the heuristic and systematic processing modes are labeled A and B in this figure. The network has three layers of simple units that perform the following computations.
Figure 2: Connectionist Network Representation of Decision Field Theory

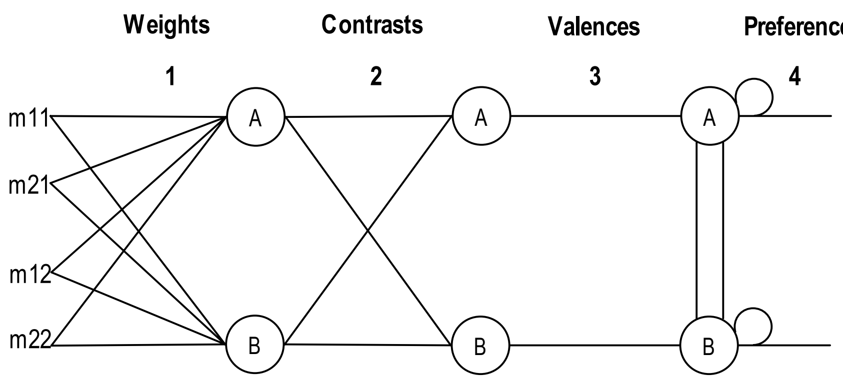


Figure 15. Connectionist Network Representation of Decision Field Theory.

The inputs into this network, shown on the far left, represent the affective evaluations of the possible consequences of a decision. These values are assumed to be generated by a motivational system (hence the symbol m_{ij}), which is not explicitly represented here (but see Busemeyer, Townsend, & Stout, 2002). For example, m11represents the positive evaluation of the consequence produced by choosing the systematic processing mode under in a negative context, and m_{12} represents the negative evaluation of the consequence produced by choosing systematic processing in a positive context. The connections, linking the inputs to the first layer of nodes, are designed to represent an attention process. At any moment in time, the decision maker is assumed to attend to one of the possible events leading to consequences for each action. For example, if the decision maker evaluates systematic processing accurate to the current context, then at that moment, option A is evaluated at m_{12} and option B is evaluated at m_{22}. However, if something comes to mind which makes the decision maker switch attention and thus the evaluated input, then at that later moment, option A is evaluated at m_{11} and option B is evaluated at m_{21}. Thus, the inputs to the first layer fluctuate from one moment (time t) to another moment (time t+h) as the decision maker's attention switches from one possible input to another. The probability of attending to a particular input at each moment reflects the decision maker's underlying subjective probability to attend to one dimension. To formalize these ideas, we define $W_g(t)$ and $W_b(t) = 1- W_g(t)$ as stochastic variables, called the attention weights, which fluctuate across time. For example, attention may be focused at time t on the proprioceptive input so that $W_g(t) > W_b(t)$, but a moment later at time t+h, attention may switch to the abstract word valence input so that $W_b(t+h) > W_g(t+h)$. The first layer of the network computes a weighted value for each option i within a set of n options as follows: $U_i(t) = W_g(t)\times m_{i1} + W_b(t)\times m_{i2} + e_i(t)$, (1).

The last 'error' term, $e_i(t)$, represents the influence of irrelevant features (e.g., in an experiment, these are features outside of an experimenter's control). The above equation looks like the classic weighted additive utility model, but unlike the classic model, the attention weights are stochastic rather than deterministic (see Fisher, Jia & Luce, 2000, for a related model). The mean values of the attention weights correspond to the deterministic weights used in the classic weighted additive model. The connections linking the first and second layers are designed to perform comparisons among weighted values of the options, to produce what are called valences. A positive valence for one option indicates that the option has an advantage under the current focus of attention, and a negative valence for another option indicates that the option has a disadvantage under the current focus of attention. For example, if attention is currently focused on event g (positive motor input), then action A has an advantage over other options and option B has a disadvantage under this state. But these valences reverse when attention is switched to event b (negative motor input). The second layer computes the valence for each option i within a set of n options by comparing the weighted value for option i with the average of the of the other (n -1) options:
$v_i(t) = U_i(t) – U(t)$, (2) where $U(t) = S\ k^1\ i\ U_k(t) / (n-1)$.
Valence is closely related to the concept of advantages and disadvantages used in Tversky's (1969) additive difference model. Note, however, that the additive difference model assumed complete processing of all features, whereas the present theory assumes a sequential sampling process that stops when a threshold is crossed. The connections, between the second and third layers, and the interconnections among the nodes in the third layer, form a network that integrates the valences over time into a preference state for each action. This is a recursive network, with positive self recurrence. Within each unit, and negative lateral inhibitory connections between units. Positive self- feedback is used to integrate the valences produced by an action over time, and lateral inhibition produces negative feedback from other actions. The third layer computes the preference state for option i from a set of n options according to the linear dynamic system: $P_i(t+h) = s\times P_i(t) + v_i(t+h) – S\ k\ ^1i\ Sik\times P_k(t)$.(3)
Conceptually, the new state of preference is a weighted combination of the previous state

of preference and the new input valence. The initial preference state, $P_i(0)$, at the start of a decision problem, represents a preference recalled from past experience. This is used to explain carry over effects from previous decisions or past experience, such as the status quo effect (Samuelson & Zeckhauser, 1988).

B. MATLAB code of DFT adapted MOVID simulations (basing on work of Busemeyer & Johnson, 2003)

In which the source code of the simulation programs is given.

Main program:

```
% set up initial conditions for 1-d diffusion
% q1 moves left, q2 moves right
% first option is first choice prob, second option is sec choice prob

clear
global a h th k del gam

k=0;            % not used in this version
a = 1;          % shouldn't need to change this;(staying probability is 1-a)
gam = 0;          % this is for feedback. 0 is perfect feedback, 1 is no feedback
h = .01;         % time step parameter. should be fine where it is.

for th = 1.2:+.1:2;             % threshold bound. for loop which sets the threshold t unit higher after every iteration
                                % with the z value
   for z = .9:-.1:.1;           % this is the initial bias. + gives bias for 2nd alt, - gives bias for 1st alt. loop for
                                % & iteration of one threshold values with z-values from -.9 to .1
      w = .1;                   % weight is given to 1st attribute, the modality
      W = [w 1-w]';
      M = [1 0;                 %1st alternative (processing mode, positive result)
             0 1];              % 2nd alternative (processing mode, negative result)
                                % columns represent the different attributes (motor vs. word valence)

% ======== MATHEMEATICAL DERIVATIONS TO FOLLOW ================

      C = [1 -1; -1 1];
      Mu2 = C*M*W;
      Mu2=Mu2(1,1);

      Psi = (diag(W) - W*W') ;
      Cov = C*M*Psi*M'*C';
      Noise = C*eye(2)*C';
      sig1 = 1; sig2 = 5;
      %sig1 = M(2,1); sig2 = M(2,2);
      Cov2 = sig1*Cov + sig2*Noise;
      Cov2 = Cov2(1,1);

      std = sqrt(Cov2);
      del = sqrt(h)*std*a;
      th_temp = th*std;
      z_temp = z*th_temp;
      L = [th z];


      ST2 = bldT2n(Mu2,Cov2,z_temp);
      [P T ] = prob2(ST2);
```

```
PPO = P(1,1);
pr = PPO;

full([P T]);
Z = ([PPO L w])
```

PROP2:

```
function [P,T] = prob2(ST)
% [P,T ] = prob2(ST)
% compute choice probability and mean response time for 1-d

global a h th k del gam

m = size(ST,2)-3;
SXT = ST(:,1:m);
SX1 = ST(:,m+1);
SX2 = ST(:,m+2);
P0 = ST(:,m+3);

ImX = speye(m)-SXT;

P1 = P0'*(ImX\SX1);
P2 = P0'*(ImX\SX2);
P = [P1 ; P2 ];

ImX2 = ImX*ImX;

T1 = P0'*(ImX2\SX1)/P1;
T2 = P0'*(ImX2\SX2)/P2;

T = h*[T1 ; T2 ];
```

BLDT2:

```
function ST = bldT2(Mu2,Cov2,z_tmp)
% ST = bldT2(Mu2,Cov2)
% 1-d transition matrix

global a h th k del gam

std = sqrt(Cov2);

k = round(th_temp/del);
Z = k+round(z_tmp/del);
m = 2*k+1;
K = m-2;

X = -(k-1)*del;
[Q Yh] = trans2(Mu2,Cov2,X);
SX1 = sparse(1,1,Q(1),K,1);
TX = [Q(3); Q(2)];
RT = 1*ones(2,1);
CT = [1;2];
X = (k-1)*del;
[Q Yh] = trans2(Mu2,Cov2,X);
SX2 = sparse(K,1,Q(2),K,1);
TX = [TX; Q(1); Q(3)];
RT = [RT; K*ones(2,1)];
CT = [CT; (K-1); K ];
```

```
for i = 2:(K-1)

   X = (i-k)*del;
   [Q Yh] = trans2(Mu2,Cov2,X);
   TX = [TX; [Q(1); Q(3); Q(2)]];
   RT = [RT; i*ones(3,1) ];
   CT = [CT; i-1; i; i+1];

end

SXT = sparse(RT,CT,TX,K,K);
% [ SXT' ; sum(SXT') ]
if sum(sum(SXT(2:K-1,:)')) < K-2
    'warning not a transition matrix any more'
end
P0 = sparse(Z,1,1,K,1);
ST = [SXT SX1 SX2 P0];
```

C. Figure & Table Captions

D. Data-Analysis Results

In which detailed SPSS results are presented.

T-Test 1

Group Statistics

	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	27	,948133	,0248195	,0047765
	negative	27	,823896	,0699842	,0134685

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	27,603	,000	8,694	52	,000	,124237	,0142904	,0955613	,1529128
	Equal variances not assumed			8,694	32,438	,000	,124237	,0142904	,0951439	,1533301

T-Test 2

Group Statistics

	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	18	,907356	,0387601	,0091359
	negative	18	,886678	,0463239	,0109186

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	,784	,382	1,452	34	,156	,020678	,0142366	-,0082545	,0496100
	Equal variances not assumed			1,452	32,974	,156	,020678	,0142366	-,0082877	,0496432

T-Test 3

Group Statistics

	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	18	,629150	,0483862	,0114047
	negative	18	,574756	,0504677	,0118954

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	,043	,837	3,301	34	,002	,054394	,0164793	,0209045	,0878844
	Equal variances not assumed			3,301	33,940	,002	,054394	,0164793	,0209023	,0878866

T-Test 4

Group Statistics

	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	27	,753867	,0505525	,0097288
	negative	27	,435037	,0636376	,0122471

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	1,272	,265	20,384	52	,000	,318830	,0156410	,2874437	,3502156
	Equal variances not assumed			20,384	49,469	,000	,318830	,0156410	,2874054	,3502538

T-Test 5

Group Statistics

	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	27	,937385	,0340506	,0065530
	negative	27	,855300	,0716311	,0137854

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	22,137	,000	5,378	52	,000	,082085	,0152637	,0514564	,1127140
	Equal variances not assumed			5,378	37,179	,000	,082085	,0152637	,0511631	,1130073

T-Test 6

Group Statistics

	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	18	,908161	,0473195	,0111533
	negative	18	,894628	,0535709	,0126268

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	,517	,477	,803	34	,427	,013533	,0168473	-,0207045	,0477712
	Equal variances not assumed			,803	33,490	,427	,013533	,0168473	-,0207238	,0477904

T-Test 7

Group Statistics

	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	18	,616811	,0524969	,0123736
	negative	18	,579500	,0540672	,0127438

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	,021	,885	2,101	34	,043	,037311	,0177626	,0012131	,0734091
	Equal variances not assumed			2,101	33,971	,043	,037311	,0177626	,0012120	,0734102

T-Test 8

Group Statistics

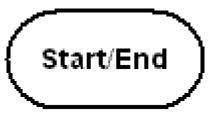
	INPUT	N	Mean	Std. Deviation	Std. Error Mean
PROB_A	positive	27	,706411	,0524428	,0100926
	negative	27	,482893	,0619951	,0119310

Independent Samples Test

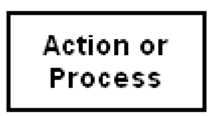
		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PROB_A	Equal variances assumed	,723	,399	14,303	52	,000	,223519	,0156272	,1921603	,2548768
	Equal variances not assumed			14,303	50,609	,000	,223519	,0156272	,1921397	,2548973

E. Basic Flowcharting Notation

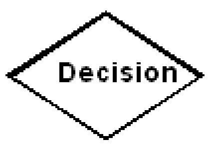
Flowcharts use special shapes to represent different types of actions or steps in a process. Lines and arrows show the sequence of the steps, and the relationships among them.



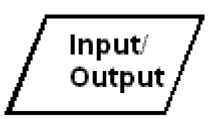
The terminator symbol marks the starting or ending point of the system. It usually contains the word "Start" or "End."



A box can represent a single step ("add two cups of flour"), or and entire sub-process ("make bread") within a larger process.



A decision or branching point. Lines representing different decisions emerge from different points of the diamond.



Represents material or information entering or leaving the system, such as customer order (input) or a product (output).

Lines indicate the sequence of steps and the direction of flow.

F. Statement

I hereby state that this thesis is was written only by me and that no additional sources except the ones stated have been used.

Nikos Green