An Integrative Formal Model for Decision Making based on Expected Utility:
The DMEU

Irene Vega Ramón

Steven Raaijmakers

University of Amsterdam Vrije Universiteit

Behavioral Dynamics in Social Networks

Project Coordinator: prof. Jan Treur

December 26th, 2019

Abstract

We develop and test the Decision Making model based on Expected Utility (DMEU), an integrative second-order adaptive temporal-causal model of decision making with a focus on a rational valuing process that considers emotions, temporal discounting, learning and its interaction with expectancy. The model is an integration of the main advances in cognitive and affective neuroscience, picoeconomics and expectancy theory. It responds to the two main challenges that are hindering the study of decision making: (a) lack of formal dynamic computational models, and (b) discipline-bound theories. Simulations of the model generate predictions regarding action prediction, adaptive time-sensitive and affective valence, and the adaptivity of expectancy through learning cycles. The model is analyzed and validated qualitatively and quantitatively. Discussion focuses on the theoretical contribution of formally integrating elements of decision making, further empirical work needed to test the model and further theoretical work needed to continue the integration process.

An Integrative Formal Model for Decision Making based on Expected Utility: The DMEU

The decision making process is key both for the understanding of human nature and for its practical impact in almost every aspect of human life. Its place at the core of natural and social sciences is observed in the multiple disciplines that have provided maintained effort on its study, among which neuroscience, psychology, and economics are salient.

Although these lines of multidisciplinary research have advanced the study of human behavior, there are two main gaps that are hindering further progress: (a) the maintained lack of integration for the conceptualization of the decision making process in the superabundance of multidisciplinary theories, each with its own nomenclature, structure, and etiology (e.g., Austin & Vancouver, 1996; Cooksey, 2001; Locke & Latham, 2004); and (b) the incomplete descriptions of the dynamics of decision making (e.g., Dalal & Hulin, 2008; Vancouver, Weinhardt, & Schmidt, 2010).

In this essay, the first challenge is undertaken by integrating current insights of the different theoretical traditions. First, in neuroscience there has been a general pledge towards the inclusion of emotions in the conceptualization of cognitive processes such as rational decision making (e.g., Pessoa, 2008; Phelps 2006). Traditionally, emotions were thought to play only a disturbing role, although generally it is now thought that cognition and emotion cannot be isolated (Loewenstein & Lerner, 2003). Specifically, emotions play a role in the valuing process of the decisions, activated in the amygdala (Phelps, 2006). For example, it has been argued that decisions with bad feelings associated with them lack robustness (Treur, 2016), and that the emotional response to stress triggers immediate action until a certain level of acuteness (Radley & Morrison, 2005).

Second, in psychology the expectancy theory, that defines motivation to act as a function of value and expectancy, has been the prominent frame since its introduction by Vroom (1964), and constantly refined since then. Nobel prize winner Akerlof (1991) further argued that the expectancy theory should be adapted to account for the salient sensitivity of humans to the present instead of the future.

Third, in economics effort has been exerted precisely in understanding the temporal dimension of decision-making (e.g., Ainslie, 1992; Green, Myerson, & McFadden, 1997), thus urging the cumulative integration of theories. Dennet & Brown (1991) has described how by evolution cognitive capabilities have developed to estimate the value of an option in the future in comparison to the value of an option in the present. However, the temporal distance of options affect the valuing process, with closer events being valued higher than distant events. In fact, intertemporal decision making has demonstrated to fit hyperbolic and exponential discounting models (Treur, 2012).

This paper integrates the advances in each of these approaches and describes the phenomenon using neutral terminology for its applicability in every field. The advances respond to empirical problems of the individual theories. For example, Van Eerde and Thierry (1996) meta-analytic study noted that the expectancy theory is weak in predicting behaviour over time. In this paper, the adaptive dynamics of decision-making with respect to learning and hyperbolic discounting greatly rectifies this weakness. Moreover, it explicitly models the effect of emotions on the valuing process to account for the empirical based emotional rationality.

The second challenge is undertaken by modelling using a temporal-causal model, a modelling approach based on causal relations that incorporates a continuous time dimension to model dynamics. This temporal dimension enables causal reasoning and simulation for networks that inherently contain cycles, that is the case for the mental modelling of the energization of behaviour. The model accounts for two types of dynamics: dynamics within the given network structure (e.g., perception of an external stimulus) and dynamics of the network (e.g., the effect that learning about the outcomes of a certain action has on the evolving of the future network). The adaptive temporal-causal network model for decision making of Treur (2016, p. 163) is used as a base and expanded to form the DMEU. The main advantage of this model is the validation it receives from neuroscientific research, including the integration of emotions as a vehicle for rationality.

Thus, the aim of the paper is to expand and test the model so that it can (a) explicitly represent the dynamics of expectancy, (b) specify the dynamic intertwined nature of valence and emotions, and (c) explicitly represent the dynamic role of hyperbolic time discounting on valuing processes. In the following section, the model is developed using insights from the different theoretical traditions. Second, the viability of the computational model is assessed by simulating it in an experiment and determining whether it can produce the predicted results. Third, the model is validated qualitatively and quantitatively. Finally, the discussion focuses on the theoretical contribution of formally integrating elements of decision making, further empirical work needed to test the model, and further theoretical work needed to continue the integration process.

1. Temporal causal networks

An adaptive temporal-causal modelling approach is used (see Treur, 2016), that is a generic dynamic modelling approach that incorporates a dynamic perspective on causal relations. The dynamic perspective is represented as an added continuous time dimension, that enables the modelling of cyclic causal graphs and the timing of causal effects. This enables the causal reasoning and causal simulation of processes that inherently contain cycles, as is the case in the cognitive-affective process of decision making.

The application of the approach begins with a conceptual representation of a process, that can take the form of a graph or a matrix. These conceptualizations facilitate the relation of the model to a wide variety of disciplines in which such causal relations are used to express knowledge. In the case of the graphical conceptual representation, states are illustrated using nodes and connections are illustrated using arrows. This indicates the impact that one state has on another. The model further represents information about the strength of the impact from state X to Y by connection weight $\omega_{X,Y} = \omega(X, Y)$, the timing of the effect of the impact by speed factor η_Y, and the aggregation of multiple impacts on a state by combination function C_Y. There are different combination functions that can be used to express the desired effect of the impact on a state (see Treur, 2012, 2016). The graphical conceptualization can be transformed into a numerical representation of the model, as illustrated in Table 1.

Moreover, the adaptivity represents the dynamics of how certain characteristics of a network structure change over time. A well-known example of such an adaptation principle concerns the adaptation of the connection weights in mental networks by Hebbian learning (Hebb, 1949), considered as a form of plasticity of the brain in cognitive neuroscience, i.e. “neurons that fire together, wire together”. Moreover, such adaptive behaviour can also be adaptive, leading to different orders of adaptation. For example, metaplasticity refers to the adaptation of the plasticity of the brain in certain circumstances. The representation of dynamic connection weights is done by considering them as states, as shown in Figure 1.

A concern of the complexities of such conceptualizations is the transparency of their representation. To account for this difficulty, the model makes use of network reification (Treur, 2019; see also Davis and Buchanan, 1980; Weyhrauch, 1980), an instrument for representing an abstract concept in a more concrete and transparent way. It does so by representing the adaptive components in an upper plane and are connected to weights or speed factors of the states in the plane below them on which they have an impact. The reified conceptual and matrix conceptualization of decision making is developed in the next section.

Table 1 Concepts of the temporal-causal network.

Concept	Representation	Explanation
State value at time *t*	$Y(t)$	For every time t a state Y has a value in [0, 1].
Single causal impact	$\text{impact}_{X,Y}(t) = \omega_{X,Y}X(t)$	At *t* state X with connection to state Y has an impact on Y, using its connection weight $\omega_{X,Y}$.
Aggregating multiple impacts on a state	$\text{aggimpact}_Y(t)$ $= c_Y(\text{impact}_{X1,Y}(t), \ldots, \text{impact}_{XK,Y}(t))$ $= c_Y(\omega_{X1,Y}X_1(t), \ldots, \omega_{XK,Y}X_k(t))$	The combination function c_Y determines the aggregated causal impact of states $X_1, \ldots, X_K$ on Y.
Timing of the causal effect	$Y(t + \Delta t) = Y(t) + \eta_Y[\text{aggimpact}_Y(t) - Y(T)]\Delta t$ $= Y(t) + \eta_Y[c_Y(\omega_{X1,Y}X_1(t), \ldots, \omega_{XK,Y}X_K(t)) - Y(T)]\Delta t$	The speed factor η_Y determines how fast a state Y is changed by the aggregated causal impact of states $X_1, \ldots, X_K$

2. The Adaptive Temporal-Causal Network Model for Decision Making

2.1. Development of the DMEU

The DMEU is an adaptive temporal-causal network model that is based on neuroscientific notions such as valuing of decisions in relation to cognitive processing and feeling, and internal simulation loops and execution loops (see Treur, 2016). Among the simulation loops, the as-if-body loops refers to the internal simulation of the bodily processes without actually affecting the body (e.g., Becker & Fuchs, 1985; Goldman, 2006), and is conceptually similar to prediction or imagination. The central part of the model occurs in the as-if-body loop that predicts the effect of the execution of the action. It is this loop what models expected utility by describing with neuroscientific terms the dynamic process of expecting, the dynamic process of cognitively and affectively valuing, and the effect of the time dimension in valuing.

Activation of behavior. The activation of behavior is triggered by an external world state. The internal process in the individual beings with sensing the world state through sensory input and subsequently internally representing it. This process is adaptive as the connections that are activated in the brain at the same time strengthen with time. This is called Hebbian learning and accounts for the plasticity of the brain (e.g., Hebb, 1949; Gerstner & Kistler, 2002). In the next part of the process, the reaction begins by responding. The first step in the response is the as-if-body loop in which the individual prepares for a possible execution (e.g., Damasio, 1994, p. 155-158; see also Damasio, 1999; Damasio 2010). This as-if body loop represents a prediction of the execution of the action.

Expectancy. It is in the first step of the as-if-body loop where predicting occurs. Neuroscientifically, predicting is the link between the preparatory state and the sensory representation of the internal simulation of executing the action. Such important connection is what in the expectancy theory it is referred to as *expectancy* (e.g., Vroom, 1964), and in picoeconomics referred to as *rate* (e.g., Ainslie, 1992). It refers to a subjective sense of probability: people are more likely to allocate resources to an action if they believe that their resources are more likely to lead to a valued outcome (e.g., Vroom, 1064; Sun, Vancouver, & Weinhardt., 2014). The key resource considered in the model is time (e.g., Ballard, Yeo, Loft, Vancouver, & Neal, 2016). Mathematically, expectancy is traditionally bounded between zero and one, with zero indicating that the event is impossible and 1 that the event will occur.

Adaptation of expectancy. Expectancy is adaptive to account for the learning process that inform future predictions based on the actual results of the execution of the action. It is memory what informs future expectancies by comparing the perception of the results of the execution of the action to the expectancies one had in the as-if-body loop. Note that it is the perception of the world state after the execution rather than the world state itself what informs the expectancy comparator, as this conceptualization has received more empirical support (Vancouver & Scherbaum, 2008).

Affective valence. Both the cognitive valence and the feeling, which is a form of affective valence, are triggered by the prediction of the results of the internal simulation of executing the action. The importance of affective rationality has been supported by recent neurological literature that addresses the issue of emotional valuing. Emotions play a role in the valuing process of the decisions, activated in the amygdala (Morrison & Salzman, 2010; Murray, 2007; Salzman & Fusi, 2010). For example, it has been argued that decisions with bad feelings associated with them lack robustness (Treur, 2016) and that the emotional response to stress triggers immediate action until a certain level of acuteness (Radley & Morrison, 2005).

The valuing function of the amygdala is not only associated with fear, in fact, parts of the prefrontal cortex and other brain areas such as hippocampus, basal ganglia, and hypothalamus have extensive, bidirectional connections with the amygdala (e.g., Ghashghaei, Hilgetag, & Barbas, 2007; Janak & Tye, 2015; Likhtik & Paz, 2015). The stimuli often leads to the associated response and the respective predicted effects and such in turn trigger rewarding or aversive emotional responses. The individual thus experiences these feelings as a form of value towards the predicted effect (Treur, 2016). As such mental connections are triggered at the same time with respect to the external stimulus, the feeling triggered by the prediction is adaptive to account for the plasticity of the brain, following again Hebbian learning (Hebb, 1949).

Cognitive valence. Cognitive valence refers to the valence resulting from cognitive states such as beliefs and desires. Beliefs are simplified as the cognitive states sensing knowledge about the world and generated mainly on the bases of sensing. They trigger emotional responses that result in certain feelings. At the same time, the reverse direction of influence occurs, as certain emotions trigger the inclination to think in ways that reinforce the emotion, thus awakening and shaping beliefs (Frijda, 199; Frijda, Manstead, & Bem, 2000).

The interaction between cognitive and affective states has been strongly supported by neuroscientific research (e.g., Eich et al., 2000), with some even defending that they are so intertwined that they might be conceptualized together as their distinction might be difficult (e.g., Phelps, 2006). Such intertwined nature is conceptualized in the model with bidirectional connection weights between both.

Adaptation of the cognitive valence. In the second reification layer, hyperbolic time discounting is applied to account for the adaptive nature of valence with respect to time. In essence, hyperbolic time discounting (Ainslie, 1992) refers to the human tendency to undervalue future events. This leads to a preference to choose less valuable but closer rewards instead of more valuable but distant rewards. The key to the theory is the formal discounting between values over time. Intertemporal decision making has demonstrated to fit both hyperbolic and exponential discounting models (e.g., Treur, 2012).

The hyperbolic-exponential discounting is modelled using the mental workload perspective (see Treur, 2012) that explains the phenomenon by positing that the value of possibilities in the future is accompanied by a certain mental workload, such as the mental burden to keep the issue in mind, worry about it, and suppress impatience. The conceptualization of the hyperbolic discounting includes the critical power, that indicates the level of power that can be provided to the activity without increasing the mental workload. Moreover, in this paper a parameter α is added, that accounts for the trait impulsiveness. This personal parameter indicates the personal sensitivity to delay, with people with a higher score in the parameter valuing more the closeness of the deadline, and vice versa, and people with a lower score being less sensitive to the time distance. In hyperbolic time discounting theories, such trait has received extensive empirical support (Petry, 2001; Richards, Zhang, Mitchell, & de Wit, 1999)[1].

Commitment. The constant valence and the repetition of the execution of a decision reinforce certain beliefs and emotions associated with the decision. Moreover, they further reinforce the execution of such decision. This commiting and habituation process is represented in the commitment stage and its further direct connections with both types of valence and execution.

Execution. A high level of expected utility for the action (captured in the as-if body loop) and a high level of commitment are the factors that trigger the execution of the action. The process is adaptive (Hebbian learning; Hebb, 1949) to account for the automaticity of certain actions when they have been triggered by preparatory states before. The action, along with external factors outside the control of the individual, both create a new world state, that the individual senses and perceives.

[1] It must be noted that hyperbolic time discounting theories have normally included a variable 'rate' to account for utility, that indicates the expectancy for the action. In this model, expectancy is modelled in the base layer as the connection weight between the preparation state for action *ai* and the sensory representation state for *w*, thus affecting valence before the hyperbolic time discounting.

2.2. Conceptualization of the DMEU

The DMEU is conceptualized graphically in figure 1. The upwards and downwards connections between states in different levels are illustrated by blue and pink lines respectively. Table 1 illustrates the overview of the (dynamic) states and adaptive connections used in the model.

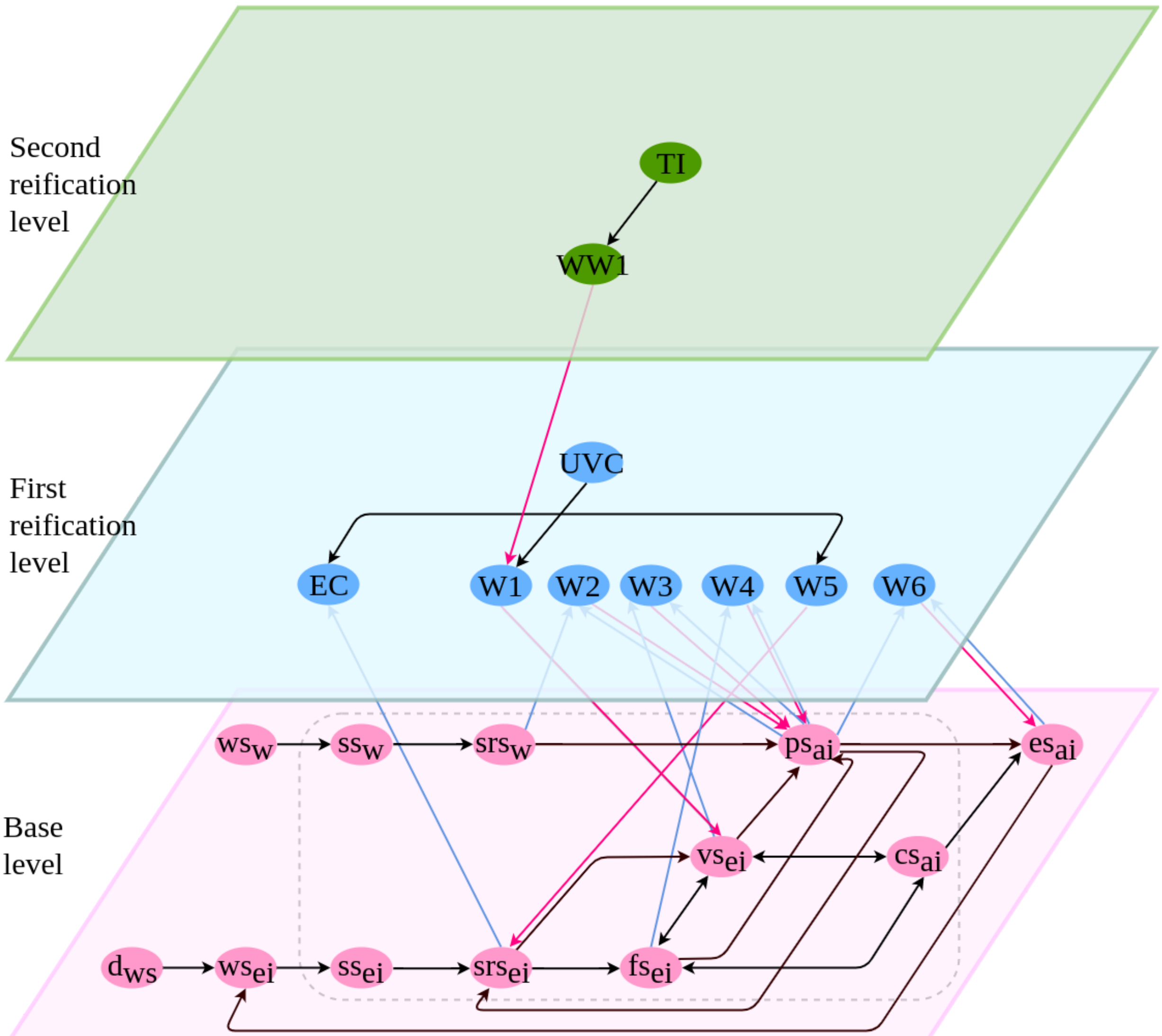

Figure 1 Graphical conceptualization of the adaptive temporal-causal network model for decision making

Table 1 Overview of the (dynamic) states and adaptive connections used in the model.

State nr.	Formal name	Informal name	Explanation	Layer
X_1	ws_w	World state for w	This characterizes the current external world situation the person is facing	Base
X_2	ss_w	Sensor state for w	The person observes the world state through the sensor state, which provides sensory input	Base
X_3	srs_w	Sensor state for effect ei	Internal representation of w	Base
X_4	ps_{ai}	Preparation state for *ai*	Preparation state for action *ai*	Base
X_5	es_{ai}	Execution state for *ai*	Execution for *ai*	Base
X_6	cs_{ai}	Commitment state for *ai*	This characterizes the level of commitment with the execution *ai*	Base
X_7	d_{ws}	Disturbance for effect *ei*	External effects on the world effect	Base
X_8	ws_{ei}	World state for *ei*	This characterizes the external world situation that occurs in consequence of the action and other external effects	Base
X_9	srs_{ei}	Sensory representation state for *ei*	An affective and cognitive valence evaluation for effect ei is generated, via the predicted sensory representation srs_{ei} for action *ai*. This provides a valuing for action *ai*.	Base
X_{10}	vs_{ei}	Cognitive valence state for effect *ei*		Base
X_{11}	fs_{ei}	Feeling valence state for effect *ei*		Base
X_{12}	ss_{ei}	Sensor state for effect *ei*	The person observes the effect ei through the sensor state, which provides sensory input	Base
X_{13}	W1	Discounted valuing criterion $\omega(fs_{ei}, vs_{ei})$	This models the adjusted intertemporal subjective value estimated for the action *ai*.	First order reification
X_{14}	W2	Weight of the amplifying connection $\omega(srs_w, ps_{ai})$	This models the relation between stimulus w and directly associated response *ai*.	First order reification
X_{15}	W3	Weight of the amplifying	This models how the generate valence	First

		connection $\omega(vs_{ei}, ps_{ai})$	effects (amplifies) the preparation for response *ai*	order reification
X_{16}	W4	Weight of the responding connection $\omega(fs_{ei}, ps_{ai})$	This models how the preparation for response *ai* affects (predicts) the representation for effect ei by considering all the psychological distance factors	First order reification
X_{17}	W5	Weight of the responding connection $\omega(srs_{ei}, ps_{ai})$	This models how the execution rate is dependent on the support or conflict between other prediction states for other goals	First order reification
X_{18}	W6	Weight of the responding connection $\omega(ps_{ai}, es_{ai})$	This models how the preparation for response *ai* affects the execution for effect ei.	First order reification
X_{19}	EC	Expectancy comparator	This models the difference between the actual results and the previous expectancy for the result.	First order reification
X_{20}	UVC	Undiscounted valuing criterion	This models the valuing criterion without adjusting it for the temporal dimension.	First order reification
X_{21}	WW1	Hyperbolic time discounting	This models the differences in value for options at present and at future time points, adjusting valence respectively.	Second order reification
X_{22}	TI	Time indicator	This indicates the objective time until deadline, i.e. when the action- if chosen- should be executed.	Second order reification

2.3. Computationalization

The proposed model can be translated into a computational temporal-causal network using the NOME template REF. In order to achieve this, the graphical representation has to be transferred to role matrices m_b**,** m_{cw}, m_{cfw}, $m_{cfp,}$ m_s and m_{iv} which can be found in table 2, 3, 4, 5, 6 and 7 respectively. The values in the role matrices are adjusted to fit the scenario described in section 4.

Table 2 Base connectivity role matrix.

M_b		1	2	3
X_1	ws_w	X_1		
X_2	ss_w	X_1		
X_3	srs_w	X_2		
X_4	ps_{ai}	X_3	X_7	X_{12}
X_5	es_{ai}	X_4	X_6	
X_6	cs_{ai}	X_7	X_{12}	
X_7	vs_{ei}	X_6	X_{11}	X_{12}
X_8	d_{ws}	X_8		
X_9	ws_{ei}	X_8	X_5	
X_{10}	ss_{ei}	X_9		
X_{11}	srs_{ei}	X_{10}	X_4	
X_{12}	fs_{ei}	X_{11}	X_7	X_6
X_{13}	W1	X_{20}		
X_{14}	W2	X_3	X_4	X_{14}
X_{15}	W3	X_7	X_4	X_{15}
X_{16}	W4	X_{12}	X_4	X_{16}
X_{17}	W5	X_{17}		
X_{18}	W6	X_4	X_5	X_{18}
X_{19}	EC	X_{11}		
X_{20}	UVC	X_{20}		
X_{21}	WW1	X_{22}		
X_{22}	TI	X_{22}		

Table 3 Connection weights role matrix.

M_{cw}		1	2	3
X_1	ws_w	1		
X_2	ss_w	1		
X_3	srs_w	1		
X_4	ps_{ai}	X_{14}	X_{15}	X_{16}
X_5	es_{ai}	X_{18}	1	
X_6	cs_{ai}	1	1	
X_7	vs_{ei}	1	X_{13}	1
X_8	d_{ws}	1		
X_9	ws_{ei}	1	1	
X_{10}	ss_{ei}	1		
X_{11}	srs_{ei}	1	X_{17}	
X_{12}	fs_{ei}	1	1	1
X_{13}	W1	X_{21}		
X_{14}	W2	1	1	1
X_{15}	W3	1	1	1
X_{16}	W4	1	1	1
X_{17}	W5	1		
X_{18}	W6	1	1	1
X_{19}	EC	1		
X_{20}	UVC	1		
X_{21}	WW1	1		
X_{22}	TI	1		

Table 4 Combination function weights role matrix.

M_{cfw}		1	2	3	4	5	6	7
		id	alogistic	step	hebb	lin_d	hyexp	ssum
X_1	ws_w			1				
X_2	ssw	1						
X_3	srs_w	1						
X_4	ps_{ai}		1					
X_5	es_{ai}		1					
X_6	cs_{ai}		1					
X_7	vs_{ei}		1					
X_8	d_{ws}	1						
X_9	ws_{ei}		1					
X_{10}	ss_{ei}	1						
X_{11}	srs_{ei}		1					
X_{12}	fs_{ei}		1					
X_{13}	W1	1						
X_{14}	W2				1			
X_{15}	W3				1			
X_{16}	W4				1			
X_{17}	W5							1
X_{18}	W6				1			
X_{19}	EC		1					
X_{20}	UVC	1						
X_{21}	WW1						1	
X_{22}	TI					1		

Table 5 Combination function parameters role matrix.

M_{cfp}		id		alogistic		stepmod		hebb		lin_d		hypexp		ssum	
		1	2	1	2	1	2	1	2	1	2	1	2	1	2
X_1	ws_w					7	2								
X_2	ssw	-													
X_3	srs_w	-													
X_4	ps_{ai}			4	1										
X_5	es_{ai}			4	1										
X_6	cs_{ai}			1	0.5										
X_7	vs_{ei}			5	0.2										
X_8	d_{ws}	-													
X_9	ws_{ei}			1	1										
X_{10}	ss_{ei}	-													
X_{11}	srs_{ei}			5	0.1										
X_{12}	fs_{ei}			1	2										
X_{13}	W1	-													
X_{14}	W2							0.9							
X_{15}	W3							0.99							
X_{16}	W4							0.85							
X_{17}	W5													2	
X_{18}	W6							0.91							
X_{19}	EC			5	0.2										
X_{20}	UVC	-													
X_{21}	WW1											0	0.005		
X_{22}	TI									-					

Table 6 Speed factor role matrix.

M_s		1
X_1	ws_w	1
X_2	ss_w	0.7
X_3	srs_w	0.6
X_4	ps_{ai}	0.5
X_5	es_{ai}	1
X_6	cs_{ai}	0.7
X_7	vs_{ei}	0.6
X_8	d_{ws}	0.5
X_9	ws_{ei}	1
X_{10}	ss_{ei}	0.3
X_{11}	srs_{ei}	0.3
X_{12}	fs_{ei}	1
X_{13}	W1	1
X_{14}	W2	0.1
X_{15}	W3	0.1
X_{16}	W4	0.1
X_{17}	W5	0.1
X_{18}	W6	0.1
X_{19}	EC	0.1
X_{20}	UVC	0.1
X_{21}	WW1	0.1
X_{22}	TI	1

Table 7 Initial value role matrix.

M_{iv}		1
X_1	ws_w	1
X_2	ss_w	0
X_3	srs_w	0
X_4	ps_{ai}	0
X_5	es_{ai}	0
X_6	cs_{ai}	0
X_7	vs_{ei}	0
X_8	d_{ws}	0.12
X_9	ws_{ei}	0
X_{10}	ss_{ei}	0
X_{11}	srs_{ei}	0
X_{12}	fs_{ei}	0
X_{13}	W1	0
X_{14}	W2	0.1
X_{15}	W3	0.1
X_{16}	W4	0.1
X_{17}	W5	0.8
X_{18}	W6	0.1
X_{19}	EC	0
X_{20}	UVC	0.4
X_{21}	WW1	0.5
X_{22}	TI	200

3. Simulations

In this section we demonstrate the results of our (computational) model for an example scenario where after we perform an analysis.

<u>Scenario context:</u>
A younger person emigrates to a new country, while not being able to speak the new language yet. During the week they attend school were all courses are taught in the foreign language forcing the person to learn the language. During the weekends, they are free from school and thus the intensity of the exporse of the new language drops. However, living in the new country still exposes the person to the new language a little.

First, the intensity of the world state is chosen to follow the behaviour explained in the scenario. This is achieved using the stepmod function creating a 7 day period with a 2 day rest. Figure 5 shows the behaviour of the world state changing over time, showing peaks and valleys, which represent the days during the week and days in weekend respectively.

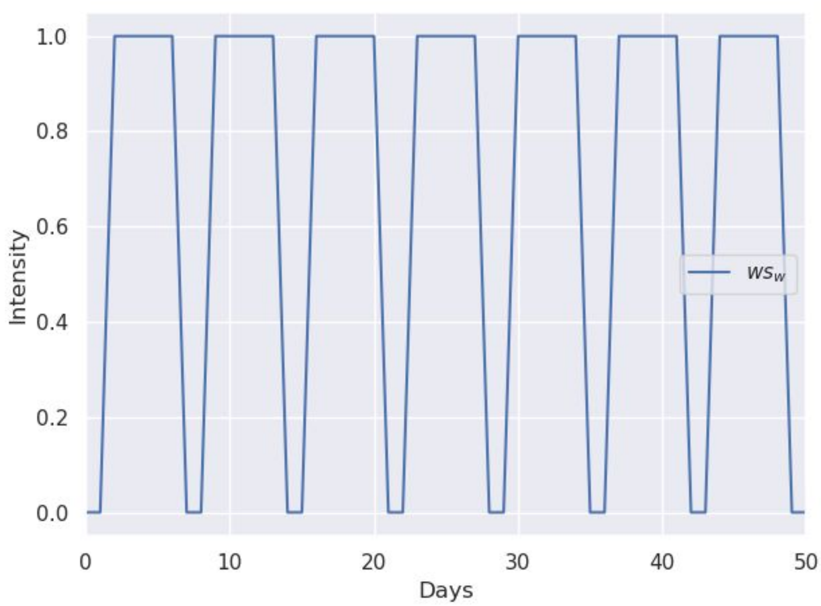

Figure 5 World state intensity over time for the scenario.

On the example scenario we perform two experiments, with Δt = 1 and *endtimeofsimulation* = 200. For both experiments we use the values from the role matrices described in section 3.3, but choose to set $\omega(es_{ai}, ws_{ei})$ to either a high or a low value. Its value can be translated to the impact or success of the execution of an action to the world.

In the first experiment we choose a high value for ω(es_{ai}, ws_{ei}), representing an action with a high success rate. In the second experiment we choose a lower value for ω(es_{ai}, ws_{ei}), representing a less successful action. After running both experiments we compare the results in order to analyze the influence of ω(es_{ai}, ws_{ei}) on the simulation over time.

Experiment 1

In experiment 1 we choose ω(es_{ai}, ws_{ei}) = 1.0. Figure 6 shows the corresponding behaviour for the states in the base layer. Note that in this figure do not visualize ws_w, ss_w, srs_w and d_{ws} since in both experiments their values will be kept the same, while leaving them out will also improve the clarity of the figure.

In the plot we notice the effect of stepmod function for multiple states, following the peaks and valleys triggered by ws_w. This effect seems to be most present for ps_{ai} while evening out for other states as we propagate further into the network. The simulation eventually leads to es_{ai} = 0.8 at t = 200.

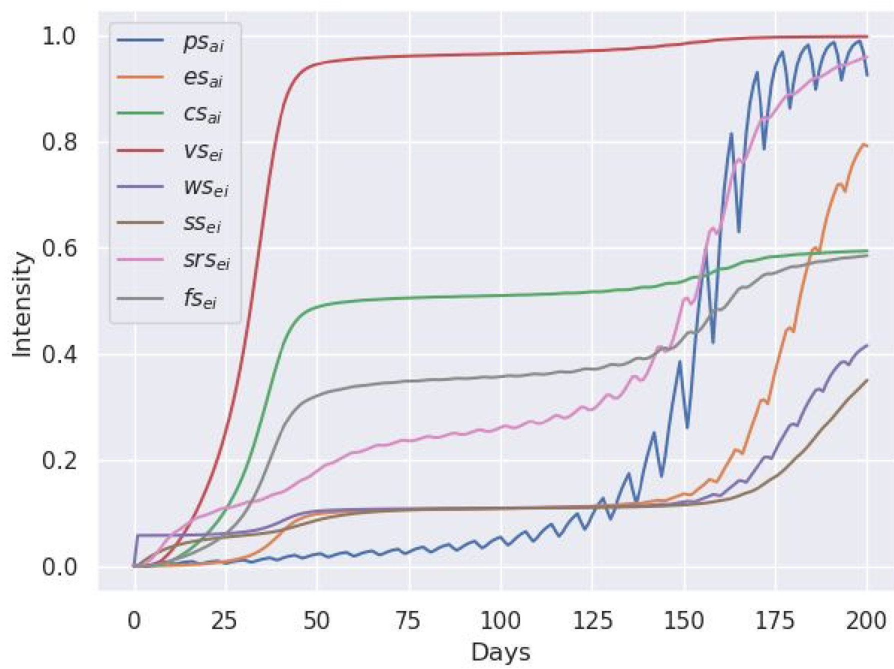

Figure 6 Intensity over time for multiple base layer states for scenario with ω(es_{ai}, ws_{ei}) = 1.0.

In figure 7, we see how the states of the first- and second layer for the same scenario behave over time. Note that the values of all states in the first- and second layer translate to a connection weight between states in the base layer.

This plot shows the effect of hebbian learning for W2 or ω(srs_w, ps_{ai}), again being influenced by the stepmod function generating input for srs_w. This effect smooths out for the other consecutive states using the hebbian learning function. Also, the discounting is visualized in this plot for WW1, starting at 0.5 for t = 0 and ending in 1.0 for t = 200, following a hyperbolic function,.

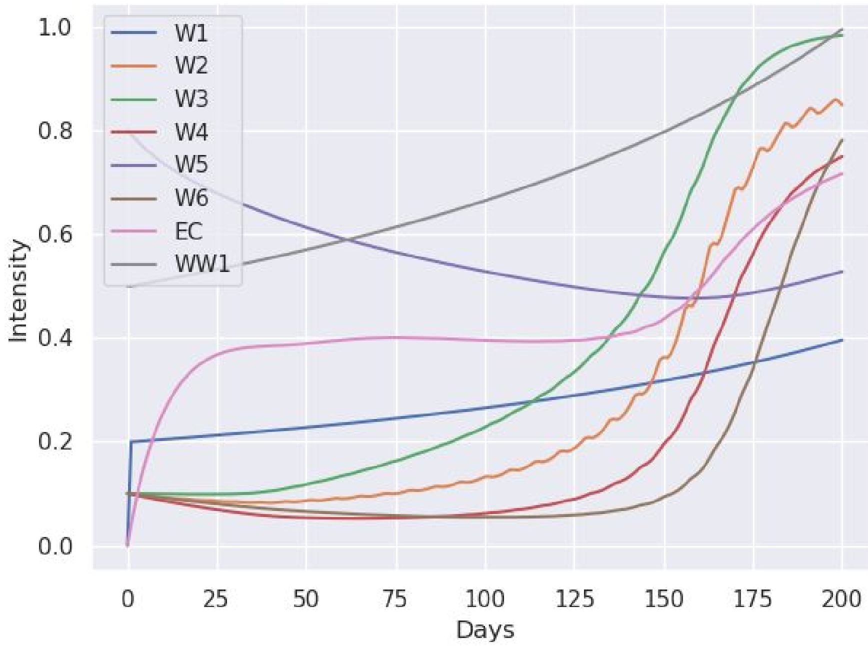

Figure 7 Intensity over time for the states in the first and second layer for scenario with $\omega(es_{ai}, ws_{ei}) = 1.0$.

Experiment 2

In experiment 2 we choose $\omega(es_{ai}, ws_{ei}) = 0.1$, representing an action with less impact on the world in comparison to experiment 1. The result of this experiment can be seen in figure 8, showing similarities with figure 6. The most noticeable difference is for es_{ai} at t = 200 having a value of 0.71 which is significantly lower than es_{ai} in experiment 1.

The corresponding first- and second layer states are visualized in figure 9. Again, this figure shows similarities with experiment 1. However, the values for W3 and W4 are lower at t = 200 which is due to those states being influenced by the value of ws_{ai}.

Comparing the results of experiment 1 to experiment 2 allows analyzing the influence of $\omega(es_{ai}, ws_{ei})$ on the course of the other states. It implies that an action having less impact on the world ensures that the intensity of the execute itself will grow slower. Besides, it also shows the dependence of the other states by ws_{ei}.

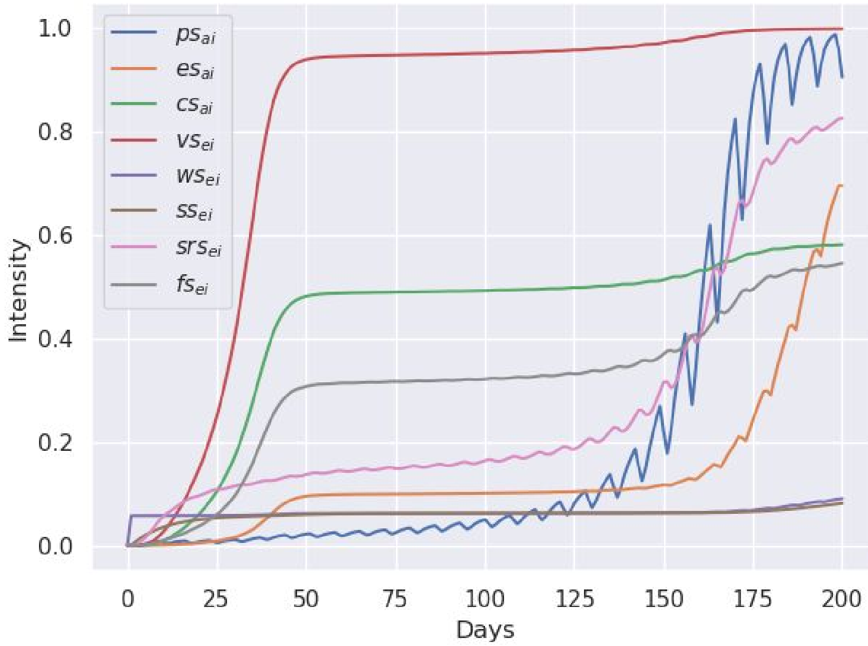

Figure 8 Intensity over time for multiple base layer states for scenario with $\omega(es_{ai}, ws_{ei}) = 0.1$.

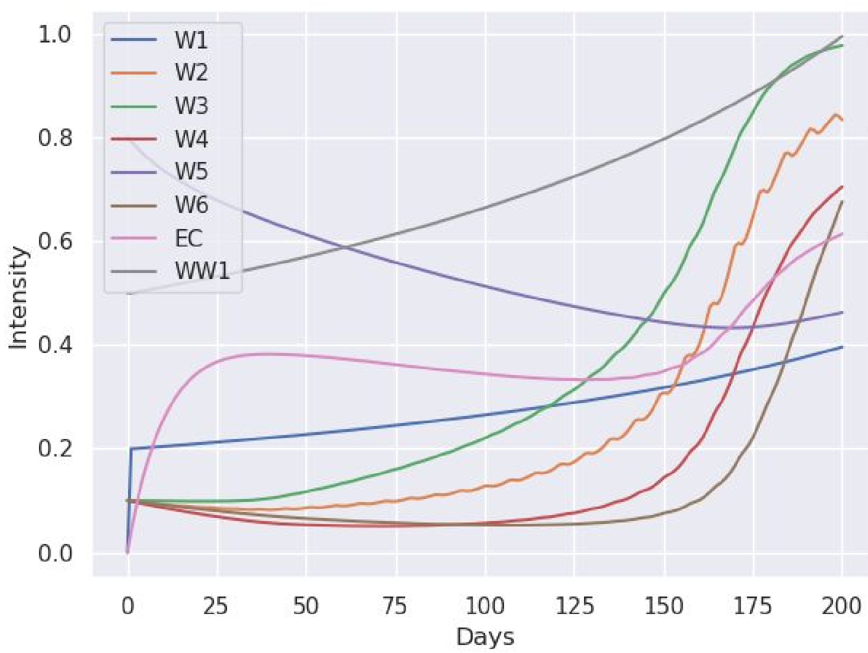

Figure 9 Intensity over time for the states in the first and second layer for scenario with $\omega(es_{ai}, ws_{ei}) = 0.1$.

4. Verification by mathematical analysis

In order to verificate our computational model we perform mathematical analysis on the example scenario described in the previous section for experiment 1. In this analysis we verify the values of states obtained by our simulation by mathematical acquired values, which can be derived using the aggimpact described in section 2 [Treur (2016, p. 326)]:

$$\mathbf{aggimpact}_{\mathbf{Y}}(t) = c_Y(\omega_{X1,Y}X_1(t), \ldots \omega_{Xk,Y}X_k(t))$$

with $X_1, \ldots X_k$ being the states with connections to Y and c_y being the combination function used for state Y.

In this analysis we focus on states that are stationary which holds for a state Y if dY / dt = 0 Treur (2016, p. 325). As shown in figure X this applies to multiple states except for ps_{ai} and es_{ai}, which seem to fluctuate around a certain value while its amplitude seems to be caused by the stepmod input from ws_w.

We choose to verify the values of cs_{ai}, vs_{ei} and fs_{ei} at t = 500 since they seem to be stationary at this point in time. First, we show the complete derivation for obtaining the error between cs_a in order to demonstrate the process. To achieve this, we need the values of states with outgoing connections to cs_{ai}, which are vs_{ei} and fs_{ei} having values 0.99845 and 0.59112 respectively at t = 500. Their connection weight to cs_{ai} are $\omega(vs_{ei}, cs_{ai}) = \omega(fs_e, cs_{ai}) = 1.0$. Knowing that cs_{ai} is using the alogistic function from NOME with $\sigma = 1.0$ and $\tau = 0.5$, we calculate the aggimpact of cs_{ai} for t = 500 as follows [Treur (2016, p. 131)]:

$$\mathbf{alogistic}_{1,0.5}\,(0.99845 * 1 + 0.59112 * 1) = 0.59563742$$

The computational simulation yields $cs_{ai}(500) = 0.59563$, resulting in an error of $7.42 * 10^{-6}$. In table X the procedure described above is repeated for states vs_{ei} and fs_{ei}. Note that in the derivation of vs_{ei} we have an adaptive connection weight in the form of $\omega(srs_{ei}, vs_{ai})$. Other than the non-adaptive connection weights this value should be interpreted from the computational simulation itself rather than from the role matrices.

The mathematical verification shows that the results of our computational model for cs_{ai}, vs_{ei} and fs_{ei} are consistent with the mathematical derivations since the errors are negligible.

Table 8 The error for different states in our model for the example scenario.

state X_i	cs_{ai}	vs_{ei}	fs_{ei}
time point t	500	500	500
$X_i(t)$	0.59563	0.99845	0.59112
aggimpact $x_i(t)$	0.59563742	0.99844655	0.59113694
aggimpact $x_i(t)$ - $x_i(t)$	$7.42 * 10^{-6}$	$3.45 * 10^{-6}$	$1.694 * 10^{-5}$

5. Parameter Tuning

Parameter tuning is a technique used to find values for specific parameters which will minimize the error between given empirical data and data produced by the simulation. However, no suitable empirical data was found regarding this model. Therefore, in this section we describe parameter tuning to achieve a value of $es_{ai} = 0.5$ at $t = 200$ using the parameter values described in the role matrices for the example scenario (table 2, 3, 4, 5, 6 and 7).

Since the DMEU contains lots of different parameters the search space is highly dimensional and complex. Therefore we restrict the set of parameters to be tuned to connection weights between states in the base layer that are non-adaptive. In table 9 the tuned values for the parameters are described. In figure 10 the effect of these values on our model is portrayed, which indeed shows that at $t = 200$ we find $es_{ai} = 0.50487$. This results in a MSE of 0.00487.

Figure 10 Values of states for tuned parameters.

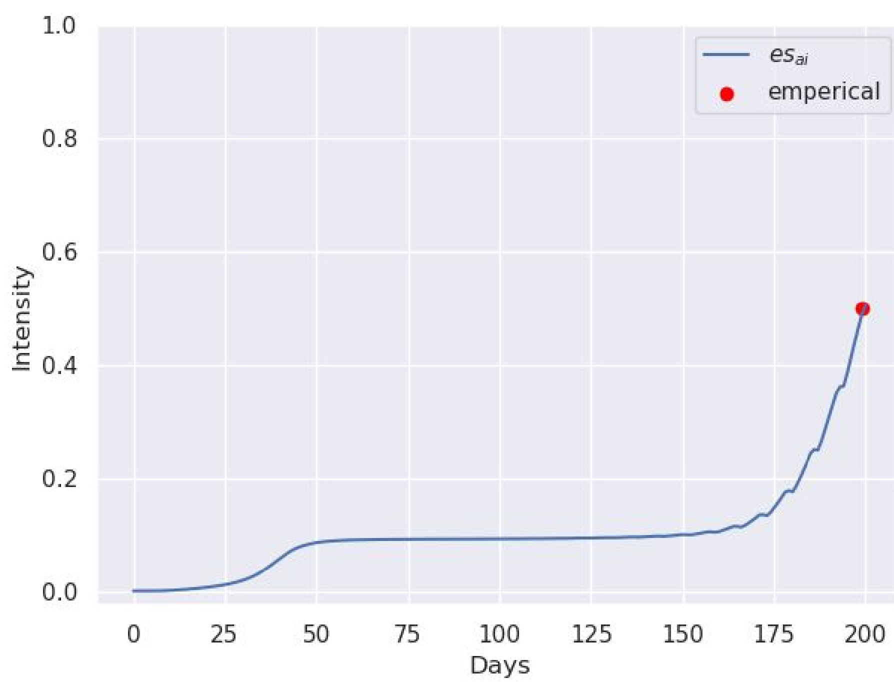

Table 9 Tuned parameters.

Param.	Val.	New val.
$\omega(ws_w, ss_w)$	1	0.9816
$\omega(ss_w, srs_w)$	1	0.9934
$\omega(cs_{ai}, es_{ai})$	1	0.9810
$\omega(vs_{ei}, cs_{ai})$	1	0.9769
$\omega(fs_{ei}, cs_{ai})$	1	0.9949
$\omega(cs_{ai}, vs_{ei})$	1	0.9897
$\omega(fs_{ei}, vs_{ei})$	1	0.9593
$\omega(d_{ws}, d_{ws})$	1	0.9982
$\omega(d_{ws}, ws_{ei})$	1	0.9812
$\omega(es_{ai}, ws_{ei})$	1	0.9622
$\omega(ws_{ei}, ss_{ei})$	1	0.9926
$\omega(ss_{ei}, srs_{ei})$	1	0.9893
$\omega(srs_{ei}, fs_{ei})$	1	0.9587
$\omega(vs_{ei}, fs^{ei})$	1	0.9919
$\omega(cs_{ai}, fs_{ei})$	1	0.9833

5. Discussion

The aim of this paper was to integrate different theoretical traditions to (a) explicitly represent the dynamics of expectancy, (b) specify the dynamic intertwined nature of valence and emotions, and (c) explicitly represent the role of hyperbolic time discounting on the dynamic valuing processes.

The DMEU accomplished these goals by developing the original temporal-causal network model for decision making based on emotion-related valuing (Treur, 2016, p. 163). The development consisted of the integration of the main insights in picoeconomics, neuroscience, and expectancy theories. In this way, the model is an explicit response to the two main gaps that were hindering progress in the field: lack of integration among different disciplines, and lack of dynamic models to account for decision making and motivational processes.

The first main contribution to literature is the use of temporal causal networks. This temporal dimension enables causal reasoning and simulation for networks that inherently contain cycles, that is the case for the mental modelling of the energization of behaviour. It further allows the modelling of two types of dynamics: the dynamics within the network (i.e. perceiving an external world state) and the adaptivity of the network itself (i.e. the evolution of the network based on learning, habituation, and the effect of time).

The second main contribution is the extensive theoretical integration. It first captures the intuitions of the expectancy theory by formally modeling expected utility as the result of dynamic expectancy and valence, that are made adaptive in learning cycles to account for the prediction of utility in the long run. Second, it contributes to the explicit modelling of both the cognitive and affective valence, the second one being generally excluded from formal and informal models in psychology and economics. This responds to neurological empirical research that demonstrates that there is a process of affective valence in the amygdala involved in motivation and decision making. Third, it accounts for the key resource of time in the intertemporal decision making process with an hyperbolic-exponential function that accounts for mental burden, power, and the impulsiveness trait. This predicted the empirically supported human preference to choose less valuable but closer rewards instead of more valuable but distant rewards.

However, this is only the beginning of a long process of theoretical integration that must capture the more specific insights that have accumulated in each discipline. Future research should focus on the neuroscientific relationship between cognitive and affective valence, and model with detail such adaptive process that here is only done generically. In addition, advances in theories of self-regulation note that the process of valence and expectancy is different for approach and avoidance goals. Further, motivation and decision making researchers denote the importance of the intertwined nature of perceived options towards multiple goals in the process of decision making. Until such integration continues, the DMEU should be empirically tested to complete the last validation result needed to inform our current stand in the progress continuum.

References

Ainslie, G. (1992). *Picoeconomics: The strategic interaction of successive motivational states within the person*. New York: Cambridge University Press.

Akerlof, G. (1991). Procrastination and obedience. *American Economic Review*, 81, pp.1-19.

Austin, J., & Vancouver, J. (1996). Goal constructs in psychology: Structure, process, and content. *Psychological Bulletin, 120*(3), 338-375. doi: 10.1037//0033-2909.120.3.338

Ballard, T., Yeo, G., Vancouver, J. and Neal, A. (2017). “An integrative formal model of motivation and decision making: The MGPM*”: Correction to Ballard et al. (2016). *Journal of Applied Psychology*, 102(2), pp.235-235.

Becker, W. and Fuchs, A. (1985). Prediction in the oculomotor system: smooth pursuit during transient disappearance of a visual target. *Experimental Brain Research*, 57(3).

Cooksey, R. (2001). Pursuing an integrated decision science:does ?naturalistic decision making? help or hinder?. *Journal of Behavioral Decision Making*, 14(5), pp.361-362.

Dalal, R. S., & Hulin, C. L. (2008). Motivation for what? A multivariate dynamic perspective of the criterion. In R. Kanfer, G. Chen, & R. D. Pritchard(Ed.), *Work motivation: Past, present, and future* (63–101). New York, NY: Routledge.

Damasio, A. (1994). *Descartes' Error: Emotion, Reason and the Human Brain*. London: Papermac.

Damasio, A. (1999). *The Feeling of What Happens. Body and Emotion in the Making of Consciousness.*. New York: Harcourt Brace.

Damasio, A. (2003). *Looking for Spinoza*. New York: Vintage Books.

Damasio, A. (2010). *Self comes to mind*. New York: Pantheon Books.

Davis, R. and Buchanan, B. (1977). Meta-level knowledge: overview and applications. In: *International Joint Conferences on Artificial Intelligence Organization*. Cambridge: Springer, pp.920-927.

Dennett, D. (2014). *Sweet Dreams: Philosophical Obstacles to a Science of Consciousness*. Cambridge: MIT Press.

Dennett, D. and Weiner, P. (1991). *Consciousness explained*. Little Brown.

Eich, E., Kihlstrom, J., Bower, G., Forgas, J. and Niedenthal, P. (2000). *Cognition and Emotion*. New York: Oxford University Press.

Frijda, N., Manstead, A. and Bem, S. (2000). The influence of emotions on beliefs. In: N. Frijda, ed., *Emotions and Beliefs: How Feelings Influence Thoughts*. Cambridge: Cambridge University Press, pp.1-9.

Frijda, N. (1993). The place of appraisal in emotion. *Cognition & Emotion*, 7(3-4), pp.357-387.

Gerstner, W. and Kistler, W. (2002). Mathematical formulations of Hebbian learning. *Biological Cybernetics*, 87(5-6), pp.404-415.

Ghashghaei, H., Hilgetag, C. and Barbas, H. (2007). Sequence of information processing for emotions based on the anatomic dialogue between prefrontal cortex and amygdala. *NeuroImage*, 34(3), pp.905-923.

Goldman, A. (2006). *Simulating Minds: The Philosophy, Psychology, and Neuroscience of Mindreading*. New York: Oxford University Press, p.2006.

Green, L., Myerson, J. and McFadden, E. (1997). Rate of temporal discounting decreases with amount of reward. *Memory & Cognition*, 25(5), pp.715-723.

Hebb, D. (1949). *The Organisation of Behavior*. 1st ed. New York: John Wiley & Sons.

Janak, P. and Tye, K. (2015). From circuits to behaviour in the amygdala. *Nature*, 517(7534), pp.284-292.

Likhtik, E. and Paz, R. (2015). Amygdala–prefrontal interactions in (mal)adaptive learning. *Trends in Neurosciences*, 38(3), pp.158-166.

Locke, E. and Latham, G. (2004). What Should we do About Motivation Theory? Six Recommendations for the Twenty-First Century. *Academy of Management Review*, 29(3), pp.388-403.

Loewenstein, G. and Lerner, J. (2019). The role of emotion in decision making. In: R. Davidson, H. Goldsmith and K. Scherer, ed., *The handbook of affective science*. Oxford: Oxford University Press, pp.619-642.

Morrison, S. and Salzman, C. (2010). Re-valuing the amygdaa. *Current Opinions in Neurobiology*, 20, pp.221-230.

Murray, E. (2007). The amygdala, reward and emotion. *Trends in Cognitive Sciences*, 11, pp.489-497.

Pessoa, L. (2010). Emotion and cognition and the amygdala: From "what is it?" to "what's to be done?". *Neuropsychologia*, 48(12), pp.3416-3429.

Pessoa (2008). On the relationship between emotion and cognition. *Natural Revised Neuroscience*, 9, pp.148-158.

Petry, N. (2001). Pathological gamblers, with and without substance abuse disorders, discount delayed rewards at high rates. *Journal of Abnormal Psychology*, 110(3), pp.482-487.

Phelps, E. (2006). Emotion and Cognition: Insights from Studies of the Human Amygdala. *Annual Review of Psychology*, 57(1), pp.27-53.

Radley, J. and Morrison, J. (2005). Repeated stress and structural plasticity in the brain. *Ageing Research Reviews*, 4(2), pp.271-287.

Richards, J., Zhang, L., Mitchell, S. and de Wit, H. (1999). Delay or probability discounting in a model of impulsive behavior: Effect of alcohol. *Journal of the Experimental Analysis of Behavior*, 71(2), pp.121-143.

Salzman, C. and Fusi, S. (2010). Emotion, Cognition, and Mental State Representation in Amygdala and Prefrontal Cortex. *Annual Review of Neuroscience*, 33(1), pp.173-202.

Steel, P. & Weinhardt, J. (2019). The building blocks of motivation. N. Anderson, D. S. Ones, H. K. Sinangil, & C. Viswesveran (Eds.), *Handbook of industrial, work & organizational psychology, 2*(3).

Steel, P. and König, C. (2006). Integrating Theories of Motivation. *Academy of Management Review*, 31(4), pp.889-913.

Sun, S., Vancouver, J. and Weinhardt, J. (2014). Goal choices and planning: Distinct expectancy and value effects in two goal processes. *Organizational Behavior and Human Decision Processes*, 125(2), pp.220-233.

Treur, J. (2012). Intertemporal Decision Making: A Mental Load Perspective. In: *Annual International Conference on Biologically Inspired Cognitive Architectures*. Berlin: Springer.

Treur, J. (2016). *Network-Oriented Modeling: Addressing Complexity of Cognitive, Affective and Social Interactions*. 1st ed. Switzerland: Springer Nature.

Treur., j. (2019). *Network-Oriented Modeling for Adaptive Networks: Designing Higher-Order Adaptive Biological, Mental and Social Network Models*. 1st ed. Warsaw: Springer Nature Switzerland AG.

Vancouver, J., Weinhardt, J. and Schmidt, A. (2010). A formal, computational theory of multiple-goal pursuit: Integrating goal-choice and goal-striving processes. *Journal of Applied Psychology*, 95(6), pp.985-1008.

Vancouver, J. (2008). Integrating self-regulation theories of work motivation into a dynamic process theory. *Human Resource Management Review, 18*(1), 1-18. doi: 10.1016/j.hrmr.2008.02.00

Van Eerde, W. and Thierry, H. (1996). Vroom's expectancy models and work-related criteria: A meta-analysis. *Journal of Applied Psychology*, 81(5), pp.575-586.

Vroom, V. (1964). *Work and motivation*. Oxford: Wiley.

Weyhrauch, R. (1980). Prolegomena to a theory of mechanized formal reasoning. *Artificial Intelligence*, 13(1-2), pp.133-170.