Affect Dynamics in Military Trainees using vMedic: From Engaged Concentration to Boredom to Confusion

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Abstract. The role of affect in learning has received increasing attention from AIED researchers seeking to understand how emotion and cognition interact in learning contexts. The dynamics of affect over time have been explored in a variety of research environments, allowing researchers to determine the extent to which common patterns are captured by hypothesized models. This paper present an analysis of affect dynamics among learners using vMedic, which teaches combat medicine protocols, as part of their military training at West Point, the United States Military Academy. In doing so, we seek both to broaden the variety of learning contexts being explored in order better understand differences in these patterns and to test the theoretical predictions on the development of affect over time.

1 Introduction

The fundamental role of emotions in learning is well accepted if not fully understood. Though findings of negative correlations between boredom and learning generally replicate [9, 29], other affective states appear to be driven by their context and duration, with confusion appearing to differ in correlation to learning by context [9, 29, 17], possibly mediated by the duration of confusion [20] and what experience induced the confusion [17].

D'Mello and Graesser's theoretical model of affect dynamics, the development of student affect over time [11], as well as their pioneering empirical work in this area [10], has brought needed attention to the study of the affective undercurrents of successful and unsuccessful educational experiences. Over the last decade, researchers have studied affect dynamics both in classroom settings using field observations [5, 16, 29] and laboratory settings using self-report [10, 11, 21].

This research has illustrated several potential benefits to better understanding affect dynamics. First, by understanding affect dynamics, we can understand not just what a learner's affect is right now but what it will be later, helping us predict a learner's eventual outcomes. Understanding the natural developments in affect can help us design interventions that reinforce positive affective transitions and reduce negative transitions. It can also help us to understand the impacts of our interventions better; we should not congratulate ourselves on a positive transition if that transition would have happened with no intervention at all.

However, in order to achieve a theoretical model of affective pathways that will be of broad use, it is important that this data used to inform these models reflects the diverse learning experiences of different learners and different learning contexts (including what learning system is being used). Understanding how affect dynamics vary – and are influenced by – different populations and contexts could be important to fully understanding the processes around affect dynamics. We already know, for instance, that the same affective state can manifest differently in behavioral terms between populations [23]. This current study investigates affect transitions, using data from *in situ* observations of learner affect, among US military cadets using vMedic, a game-based virtual environment that provides training in combat field medicine, representing a different population, domain, and type of interaction than in previous work on affect dynamics. Affective states observed included boredom, confusion, engaged concentration (flow), frustration, surprise and anxiety.

2 Previous Research

2.1 Cognitive-Affective Learning

Researchers have long hypothesized a set of basic emotions (e.g., happiness, sadness, anger, disgust, fear, and surprise, [14]), but, as Table 1 summarizes, those working in

Table 1. Affective states studied in previous research on affect dynamics in online learning environments. Categories considered in the current study are highlighted in gray.

	D'Mello & Graesser, 2012	D'Mello et al., 2009	McQuiggan et al., 2010	Andres & Rodrigo 2014	Guia et al., 2011	Rodrigo, 2011	Rodrigo et al., 2009	Rodrigo et al., 2010	Bosch & D'Mello, 2013	Baker et al., 2010
Anger		x	x							
Anxiety		x	x							
Boredom	x	x	x	x	x	x	x	x	x	x
Confusion	x	x	x	x	x	x	x	x	x	x
Curiosity		x								x
Delight	x			x	x	x	x	x		
Disgust		x								
Eureeka		x								
Excitement			x							
Fear			x							
Flow	x		x	x	x	x	x	x	x	x
Frustration	x	x	x	x	x	x	x		x	x
Happiness		x								
Neutral		x			x	x	x	x		
Sadness		x	x							
Surprise	x	x		x	x	x	x			x

education domains typically focus on cognitive/affective states more common to learning contexts and thought to correlate to learning outcomes (e.g., [18]). These typically include boredom, confusion, engaged concentration (the affective state related to Csikszentmihalyi's construct of flow [8]), delight, and frustration, but may also include a range of other states (e.g., [12, 21]).

2.2 Affect Dynamics

One of the more prominent theories about the temporal dynamics of affect is D'Mello & Graesser's [11] hypothesized model of affect dynamics for learning (shown in Figure 1 and summarized in Table 2). Based largely on Pekrun's [25] control-value theory, this model suggests multiple possible pathways between engaged concentration (Csikszentmihalyi's [8] flow), surprise, confusion, delight, frustration, and boredom. As Figure 1 illustrates, disequilibrium (experienced as confusion) plays a central role in this model, capturing the longstanding and ever-growing body of work showing the importance of confusion to learning (e.g., [9, 17, 20, 29]).

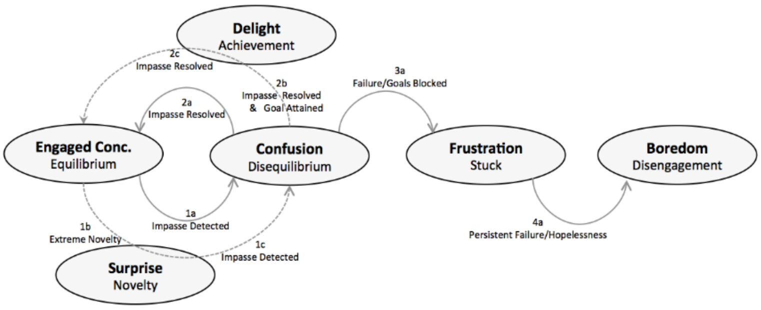

Fig. 1. D'Mello & Graesser's [11] posited model of affect dynamics during learning, adapted from Control-Value Theory.

Table 2. Summary of D'Mello & Graesser's [11] hypothesized pathways. Pathways hypothesized in Figure 1 are shown, labeled, in this transition matrix; pathways that are not part of this model are shown in gray-scale.

	to BOR	to ENG	to CNF	to DEL	to FRU	to SUR
fr. BOR						
fr. ENG			1a			1b
fr. CNF		2a		2b	3	
fr. DEL		2c				
fr. FRU	4					
fr. SUR			1c			

Empirical research in affect dynamics, however, has found that other pathways may be common. D'Mello & Graesser [11] report two studies alongside their theoretical model. The first finds that only three of the hypothesized transitions (1a, 2a, and 3) occur at levels above chance, along with one pathway that was not hypothesized (boredom to frustration). The second finds empirical evidence for four of their hypothesized pathways (1a, 2a, 3, and 4), but also evidence for two pathways that were not hypothesized (boredom to frustration as well as frustration to flow). Other studies have also failed to closely match this theoretical model. For example, Rodrigo's [26] study of affect during Mathblaster found compelling evidence for only one of the hypothesized pathways (confusion to flow), and Guia et al., [16] found that in SQL-Tutor the hypothesized pathway of confusion to frustration was less likely than chance, while other hypothesized pathways were not significant at all.

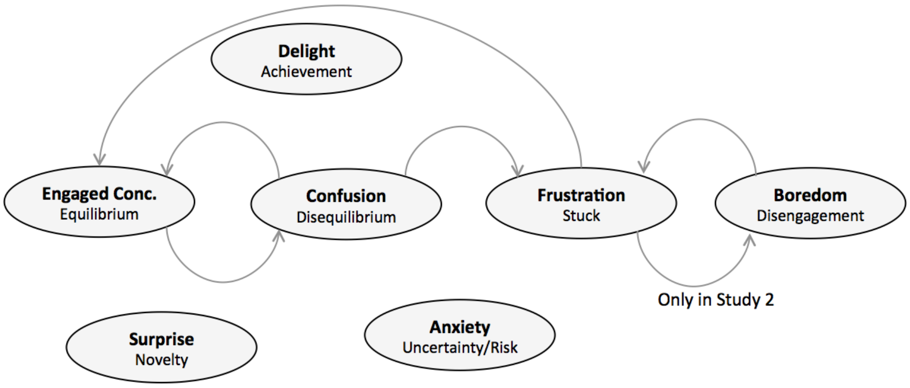

Fig. 2. Pathways found in D'Mello & Graesser's (2012) empirical research.

Much of the other research on affect dynamics has differed from D'Mello & Graesser [11] by including self-transitions (when a learner remains in the same affective state from one observation to the next) in calculations. Baker, D'Mello, Rodrigo, & Graesser [2] found that boredom and engaged concentration were likely to be persistent, across three different learning environments. In another study, Rodrigo et al., [30] found only engaged concentration was likely to show persistence, while a similar study by Rodrigo et al. [28] found persistence for boredom, confusion, and engaged concentration. Andres and Rodrigo [1] found persistence for confusion, engaged concentration, and frustration, but Guia et al. [16] found no affective states were significantly more likely than chance to persist.

The picture becomes more complicated when additional affective states are included in the research. For example, Andres and Rodrigo [1] considered all of D'Mello and Graesser's [11] affective categories (boredom, confusion, delight, engaged concentration, delight, frustration, and surprise) when studying Physics Playground [31]), but also added six others (angry, anxious, curious, happy, pride, and sad). Likewise, McQuiggan et al. [21], working in the context of a narrative environment (Chrystal Island), consider ten affective states, including six of those in D'Mello and Graesser's [11] model (anxiety, boredom, confusion, delight, engaged concentration, and frustration) and four that were not (anger, excitement, fear, and sadness). Coding with expanded lists of affective states may change the base rates of observed affective categories. Furthermore, using expanded lists of affective states may qualitatively change the nature of the coding in ways that are not fully captured by mathematical modeling.

3 Methods

3.1 Learning Environment and Participants

The learning environment observed in this study was vMedic (a.k.a. TC3Sim), a virtual world developed for the US Army by Engineering and Computer Simulations (ECS, Orlando Florida), which provides training in combat medicine and battlefield doctrine around medical first response. The system is administered through the Army Research Laboratory's modular GIFT framework [15]. In this study, 108 West Point cadets (ages of 18-22) were observed using the vMedic system (shown in Figure 3).

Fig. 3. Screenshot of vMedic scene where learner is expected to treat a combat victim.

3.2 Observation Protocol (BROMP)

While trainees used vMedic, their affective states were observed and recorded using the Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP 2.0; [24]). BROMP is a momentary time sampling method where learners are observed individually, in a pre-determined order. This ensures that each learner in an observation session is observed at roughly the same frequency as all of his or her peers. Observations are conducted by a BROMP-certified coder using HART, an android application which enforces the sampling method and automatically provides a time stamp for each observation. Observers record two distinct, but simultaneous observations about each learner: his or her behavior (usually on-task, on-task conversation, off-task, or gaming the system) and his or her affective state (usually boredom, confusion, engaged concentration, delight, and frustration). Because of the nature of momentary time sampling methods, affective states which are brief in nature (e.g., Eureka moments) are typically more difficult to capture using BROMP, but it is possible to modify BROMP coding schemes to accommodate relevant constructs that may be environment-specific (e.g., [23]).

In this study two BROMP-certified observers coded for several of the more educationally common affective states (boredom, confusion, engaged concentration, frustration). Additionally, observers coded two constructs that are not typically used in BROMP coding schemes, surprise and anxiety. In this context, surprise reflected novel and unexpected experiences within the virtual world, such as an insurgent appearing from behind a building, rather than reflecting surprise with the learning content. Likewise, anxiety was related to (but distinct from) the observations that were coded as frustration. This distinction reflects previous research on fear and anger (e.g., [19]). vMedic often presents trainees with difficult or unresolvable medical situations, triggering a variety of different affective responses. Affective expressions by a learner that suggested caution or vigilance were coded as anxiety while those that reflected annoyance or defeat were coded as frustration.

3.3 Data & Analysis (D'Mello's L)

In total, 756 of individual observations of affect were recorded: 12 anxiety, 73 boredom, 174 confusion, 435 engaged concentration, 32 frustration, 29 surprise. The number of trainees being coded during these observations varied slightly from one observation session to the next, impacting the time it takes for an observer to return to a given learner. That is, the more learners being observed, the more time between observations of an individual learner, but on average, each learner was observed once every 122 seconds (stddev = 100.14). In general, the different methods employed for collecting data for affect dynamics research has resulted in data with a variety of characteristics, with some studies using a protocol like this one, leading to regular but fairly lengthy gaps between observations. Other studies have used field observation protocols with many more observers, leading to denser observation but stronger observer effects. Still other studies have used voluntary self-report data, which sometimes is more continuous and other times is more fragmented, depending on the learner's willingness and ability to identify and express their emotions.

In order to examine the common pathways from one affective state to the next, we calculated D'Mello's L, the likelihood that a given affective state will transition to another affective state, [13]):

$$L = \frac{P(NEXT|PREV) - P(NEXT)}{(1 - P(NEXT)}$$

This metric is conceptually similar to Cohen's Kappa, comparing a transition's frequency to the base rate of the affective state that is transitioned into. A value of zero for D'Mello's L indicates that a transition occurs no more frequently than would be expected from the overall proportion of time the destination affective state occurs. Values greater than zero indicate frequencies greater than chance, taking that base rate into account, with a value of one indicating that a specific transition always occurs. Values less than zero indicate a transition that is less likely than chance, with possible values of negative infinity. It is possible to determine whether a transition is statistically significantly more or less likely than chance by calculating a value of D'Mello's L for that transition for each learner, and then comparing those values of D'Mello's L to 0 (chance value) using a t-test for one sample (cf. [5]). Benjamini and Hochberg's [6] post-hoc corrections are used here to adjust for conducting large numbers of comparisons.

4 Results

As discussed above, BROMP observations resulted in 756 observations, corresponding to 450 transitions (e.g., from anxiety to engaged concentration or from engaged concentration to confusion). Table 3 presents totals for each transition, which was then analyzed using D'Mello's L.

Table 3. Transition matrix for the current study. Anxiety, which was not considered in D'Mello & Graesser's (2012) model, is highlighted in dark gray.

	to ANX	**to BOR**	**to FLO**	**to CNF**	**to FRU**	**to SUR**	*total*	
fr. ANX	**0**	1	5	1	0	0	*7*	*2%*
fr. BOR	1	**0**	27	175	4	3	*210*	*47%*
fr. FLO	4	32	**0**	61	14	10	*121*	*27%*
fr. CNF	2	9	51	**0**	8	7	*77*	*17%*
fr. FRU	2	1	5	4	**0**	0	*12*	*3%*
fr. SUR	0	5	14	4	0	**0**	*23*	*5%*
total	*9*	*48*	*102*	*245*	*26*	*20*	***450***	
	2%	*11%*	*23%*	*54%*	*6%*	*4%*		

Results are presented in Table 4, using the same format as the presentation of previous research findings discussed above, for comparability (plus the category of anxiety – ANX). Only statistically significant results (given post-hoc controls) are reported, and those transitions that are statistically less likely than chance are given in red.

Table 4. D'Mello's L values for the likelihood of transitions within vMedic. Only statistically significant results given post-hoc controls are reported, with transitions less likely than chance given in red. Pathways that were not predicted in D'Mello & Graesser's [11] model are given in gray, including pathways for anxiety, which are highlighted in darker gray.

	to ANX	to BOR	to FLO	to CNF	to FRU	to SUR
fr. ANX				-0.268		
fr. BOR		-0.135		**0.325**		
fr. FLO		**0.114**	-0.916	**0.401**		
fr. CNF			**0.375**	-0.358		
fr. FRU		-0.078			-0.066	
fr. SUR	-0.022					

In total, we found 11 statistically significant transitions, but only four (shown in Figure 3) were more likely than chance. Two of these reflect the hypothesized central role of confusion in learning (engaged concentration to confusion, L = 0.401 and confusion to engaged concentration, L = 0.375). There was also two links that had not been previously reported: a transition from engaged concentration to boredom (L = 0.114) and a transition from boredom to confusion (L = 0.325). The link from engaged concentration to boredom suggests that vMedic is relatively unsuccessful at keeping learners engaged in a sustaining fashion (though it is unclear if this is due to features of the game or features of the population using it); however, the link from boredom to confusion suggests that enough events occur during gameplay to prevent boredom from becoming an enduring problem, unlike in other environments (e.g. [2]).

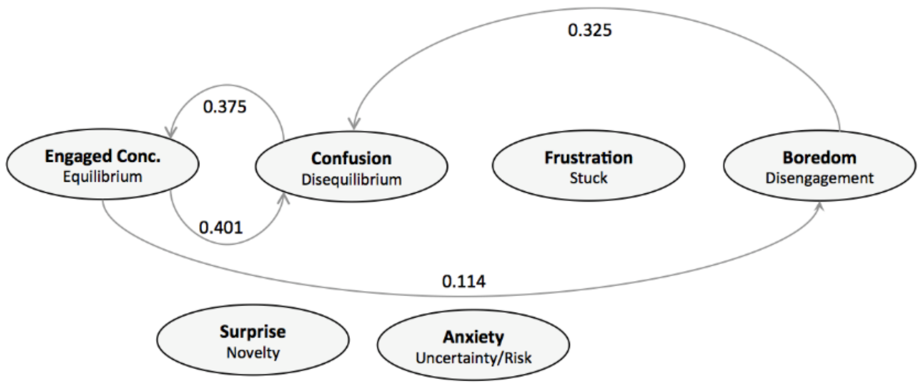

Fig. 3. Pathways found to be (positively) statistically significant in the current study, including the hypothesized loop between flow and confusion and the previously not hypothesized loop between flow and boredom.

Results for transitions that occur at levels below chance are shown in Figure 4. Note that this figure includes one of the transitions hypothesized in D'Mello and Graesser's [11] model to be more likely than chance, the transition from frustration to boredom.

Contrary to that model, this transition was statistically significantly less likely than chance in vMedic, L = -0.078. This result may be due to the population of Army cadets, who may be better able to regulate their responses to otherwise frustrating events than previously studied populations (e.g., middle-schoolers). Learners were also less likely to be anxious after being surprised, and less likely to be confused after being anxious, results which are statistically significant despite the relative infrequency of anxiety in this data set.

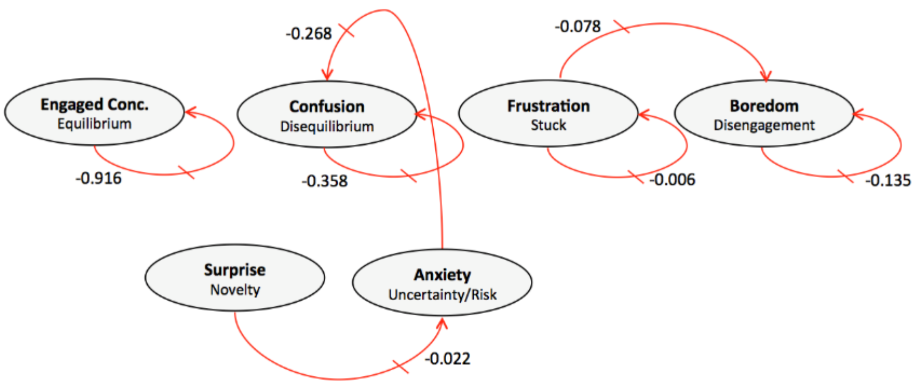

Fig. 4. Pathways found to be statistically less likely than chance in the current study.

One additional finding that is curious is the relatively low probability of learners staying in their current affective state, with self-transitions (a transition from a state to itself) being less likely than chance for all four of the most commonly studied affective states (boredom, engaged concentration, frustration, and confusion). This pattern is in contrast to most of the previous work on affect dynamics (e.g., [1, 26, 28, 30]), and may result from a combination between the fast pace of activity in vMedic, where learners switch activities with fairly high frequency, and the sampling rate of the BROMP method. However, it is worth noting that the former is a variable that has not been well controlled for in previous studies and that the latter has also varied widely from one research condition to another.

5 Conclusions

In this paper, we study the dynamics of affect within the simulation vMedic, using BROMP field observation to measure affect, and conducting statistical significance testing on whether the D'Mello's L metric is different than zero across students, to determine which transitions are significantly less or more likely than chance. Our results differ from previous published results and a key theoretical model in showing a link from engaged concentration to boredom, a link from boredom to confusion, and the lack of a hypothesized link from frustration to boredom. In general, the difference of these results from this past work is probably attributable at least in part to differences between the populations (military cadets learning material relevant to their future compared to K-12 populations or undergraduates in lab studies learning material that is relatively arbitrary to them). A military cadet might be expected to have better self-regulatory skill than the other populations studied in the past, preventing frustration from becoming boredom. However, a military cadet might also be less engaged by a game than other populations, leading the fun of the game to quickly turn boring. We also find relatively low persistence of affect between observations, another contrast to past work. We hypothesize that this may be due to the relatively fast pace of change of activities within vMedic compared to many of the other environments studied.

Investigating these hypotheses is a valuable area for future work. But the broader question is: what factors determine the differences in affect dynamics between contexts and studies? With a range of published studies on affect dynamics, we see a range of patterns – and relatively few of those patterns are consistent across studies or consistent with the one theoretical model published (e.g. [11]). Ultimately, it becomes worth asking whether affect dynamics are entirely contextual, or whether there are some patterns that reliably cut across studies. To the extent that affect dynamics *are* contextual, we need to ask what factors in the context best determine the patterns seen – is it the population? The system they are using? The design of the study? The method for measuring affect? The characteristics of individual students?

Determining the answer to these questions will be necessary to achieve the goals originally set for affect dynamics research, including the development of interventions that can improve learning outcomes. They will also allow us to build a more comprehensive theory of how affect develops and unfolds over time.

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