The Affect Effect: Integrating Student Emotions into the Design of Engineering Technology Courses with Optimization Method

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***Abstract*—This Innovative Practice Full Paper presents a study that enhanced both cognitive and non-cognitive learning outcomes through optimizing science, technology, engineering and math (STEM) students' affective responses. Much of engineering education has focused on designing courses and curriculum to maximize both cognitive and, increasingly, non-cognitive learning outcomes. The role of affective outcomes, such as feelings or values, have been comparatively under-studied in the engineering context [1]. This despite the fact that there is promising research in both educational psychology and computer science that links positive affect with enhanced learning outcomes[2, 3].**

To design a study based on affect, an engineering professor partnered with an advanced undergraduate psychology student to develop a model for capturing and applying affective outcomes in applied engineering courses. To measure affect, we collected weekly surveys of the students' affective responses to both the mode of delivery and nature of the content using categories such as boredom, surprise, and confidence, each of which have been identified as potentially significant by other researchers. We then integrated the students' responses into a predictive linear recursion model, which was, in turn, used to make curricular decisions periodically throughout the semester. In other words, the students' affective responses were used to influence the content and the delivery of the course as it was being taught.

Our findings suggest that using this predictive model to optimize affective responses could be used as the basis of responsive course design and the enhancement of student learning outcomes. The study has implications for the further study of the role of affective outcomes in engineering education; as well as the advancement of co-created (with students) models of instructional and curricular design that incorporate affective variables.

Keywords—Affect, Linear Recursion Model, STEM, Optimization

I. Introduction

A. Background

Much of engineering education has focused on (re-) designing courses and curriculum to maximize both cognitive and, increasingly, non-cognitive learning outcomes. These latter, including traits such as persistence, curiosity, and hope, have been identified as particularly salient to the retention and success of under-represented populations in STEM. The role of affective outcomes, such as feelings, attitudes, or values, while often linked to both cognitive and non-cognitive traits, have been comparatively understudied in the engineering context. This despite the fact that there is promising research in both educational psychology and computer science that links positive affect with enhanced learning outcomes [4, 5]. The current study suggests a mathematical model that not only links student affect to pedagogical modalities, but further suggests how these linkages can be optimized as the basis for long-term course design/re-design in engineering technology.

B. Literature Review

Educational scholars have long argued for the significant role that affect plays in learning. In the 1960s and 70s, Benjamin Bloom, for example, included both cognitive and affective domains in his well-known pyramids of learning, though it is the former rather than the latter with which most people are familiar [6]. Starting in the 1990s, Dee Fink's seminal conception of "significant student learning" includes almost equal attention to affective and cognitive attributes, which he depicts together in the form as a mutually reinforcing circle rather than a more hierarchical pyramid. Most recently, Sara Rose Cavanaugh synthesized several decades of scientific research on the connections between emotion and learning in her best-selling book, *The Spark of Learning* [7], in which she makes the case that cognitive and affective learning function as overlapping networks within the brain.

Despite these scholarly endorsements, the affective domain has not benefitted from the same degree of attention as the cognitive. This may be due, at least in part, to how challenging affect is to assess, and by extension, to study [8, 9]. Affective constructs are complex, changeable, and highly varied [10]. When considering attitude towards a given class, subject or instructor, for example, a student could be simultaneously happy, sad, confused, bored, surprised, distracted, enthusiastic and much more, all to varying degrees, and subject to change at any given moment. Even if these constructs could be

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appropriately categorized, they would be difficult to capture. Most studies of affective learning rely on student self-report of emotion, but Bloom describes the highest level of the affective pyramid as "characterizing", or the ability to consistently and effectively articulate affective components of students' own learning. In other words, the ability of students to accurately and authentically self-report their own emotions is a skill that must be learned and practiced. Their ability to report on affect is further compounded by how intertwined affective, cognitive, and behavioral constructs are. To put it differently, a novice learner is likely to struggle to articulate the extent to which they have learned something because of how they feel, how they think, or what they do.

Despite these challenges, research on affective learning has experienced a resurgence of interest within the particular context of STEM fields [11]. Faced with the looming STEM crisis, researchers have re-discovered the role affect, especially in the form of attitudes and values, can play in enhancing motivation and increasing persistence through STEM majors [12-14]. As an example of negative affect, several studies have confirmed that female STEM students tend to have higher levels of anxiety, including both general and specific (e.g. test-related), than their male counterparts, and that anxiety contributes significantly to attrition [15-16]. Similarly, researchers have identified the lack of a sense of belonging, defined as an emotional sense of inclusion and acceptance, as a recurring factor that impedes motivation and, by extension, student success in STEM majors, but is perhaps most salient for women and other under-served populations [17-20]. The lack of a sense of belonging is compounded by persistent stereotypes of relevance, isolation, and gender (e.g. the lone, male mad scientist), which were found to have affective influence regardless of the context or composition of a given course [3,21].

The concept of belonging has also been raised in the context of on-line courses, for which instructors have had to be intentional about cultivating an affective sense of community and presence in the absence of physical proximity [2,22-25].The study of this intentionality has been strongly influenced by research on the role of emotions in on-line gaming and/or virtual reality simulations [26, 27]. Taken collectively, this body of work has led to the identification of more stable affective constructs, even for highly complex emotional states or processes [28]. A recent landmark study, for example, measured the degree to which empathy for a given population (in this case, the homeless) could be cultivated through virtual, rather than physical interactions [29]. Online researchers have also benefitted from new methodological approaches to studying emotion made possible by machine learning. Tools such as linguistic or sentiment analysis, for example, allow for the identification of both implicit and explicit emotional expressions embedded throughout a given on-line course or courses [30-31]. These methodological innovations have enabled researchers to posit increasingly complex models of the interplay between affect and learning.

In one of the mostly widely adopted of these models, MIT researchers Kort, Reilly, and Picard (2014), propose a four-quadrant learning model, in the form of a spiral (Fig.1), which depicts the affective stages through which a student navigates a given learning experience, extending through the positive affect of curiosity aroused by initial investigation (Quadrant 1), to the confusion when initial investigation generated contradictory results (Quadrant 2), which can lead to growing frustration, even un-learning, if reinforced (Quadrant 3). The process concludes with the satisfaction associated with deeper learning (Quadrant 4).

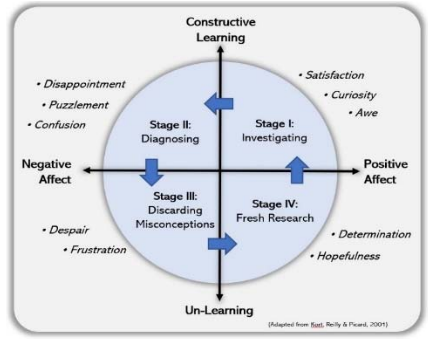


Fig.1. Kort et al learning spiral model

In the learning spiral model, the authors propose that each affective stage of the learning spiral should be paired with appropriate instructional strategies. After presenting the material (Quadrant 1), for example, the instructor may need to spend more time presenting examples to help students understand the information through repetition. Otherwise, the student may become confused, move into quadrant III, and experience negative emotions such as frustration and boredom [32]. If the student does shift into unlearning, they will likely be resistant to the introduction of new content until the reasons for the frustration can be resolved. Once these issues are resolved, however, the student becomes open to new ideas and insights, and the spiral begins again. IV. As the student moves up the spiral, cycle after cycle, he or she would experience increasingly positive affect, which manifests as both competence and confidence.

That being said, the researchers who developed the Kort model indicated that more work needs to be done to "re-engineer" pedagogy so that it can maximize both student affect and learning [1]. For our study, we have endeavored to re-engineer the instruction in two undergraduate engineering technology courses. To do so, we have used the learning spiral model as the starting point to chart a learner's emotional evolution throughout the learning process, both in the short run (a course section, or module) and in the long run (the course as a whole).

II. The Study

A. Method

Our study started as a partnership between an engineering professor and an advanced undergraduate psychology student, who worked together to develop a model for capturing and applying affective outcomes in applied engineering courses (part of a four-year degree program in Engineering Technology). These courses are offered at a remote location of a large, public, research university located in the northeastern part of the United States. The major is among the most popular offered at the relatively small branch campus, with class sizes averaging 15-25 students, the majority of whom are first-generation, traditionally aged, and male. The program has relatively high transfer rates, especially from the branch to the main campus.

To measure affect, the research team received approval from the institution's ethical review board to administer weekly surveys of the students' affective responses to the content of each course session, using constructs such as boredom and surprise, each of which correspond to a different quadrant within the learning spiral model. These were supplemented with similarly scaled items in which students rated their interest in theoretical versus application-oriented content. The survey items are based on a modified version of the CAP perceived learning scale, which consists of nine (9) validated Likert-scale measures of cognitive, affective, and psychomotor perceptions of learning [33]. In addition, the scaled survey items were supplemented with open-ended questions which were tailored to allow students to expand on their affective responses to specific topics and lessons taught that week. For the pilot study, paper surveys were administered by the undergraduate co-researcher for the first several weeks of instruction, but due to unforeseen circumstances related to COVID-19, the final three iterations were administered in an online format.

Students completed their first survey at the beginning of the course, prior to the start of instruction, and these measures served as the baseline for subsequent calculations in the model. They then completed surveys on a weekly basis and data collected from each subsequent iteration was added to the model. To strengthen the replicability of our results, these surveys were administered to students in both upper and lower division courses over the course of a semester. We then integrated these responses into a predictive linear recursion model, which was, in turn, used to make curricular decisions periodically throughout the semester. In other words, the students' affective responses were used to influence the content and the delivery of the course both as it was being taught, using an iterative feedback loop based on reported affect.

B. *Affect Prediction Model*

In this paper, our model spans previously-identified primary affects including students' preference for theory or application lectures. The model we implemented was based on dynamic programming. A stepwise linear recursion model was used to predict affective states, with theoretical section time as an independent variable. We proposed a model of affect prediction, focusing on how we could best use students' self-reported affects to proportionally split each lecture into a theoretical section and an application section, since we wanted to maximize students' affective states when a semester ends. The proposed optimization model considered the course syllabus schedule as well as the students' affective states and learning preferences. Learner preference includes whether a student likes or dislikes theory lectures and application lectures, on the basis of prior experience.

For the sake of simplicity, our model included only 6 major factors to be taken into account in predicting students' affective state in each lecture. The affect model included four basic learning affects: boredom, confusion, satisfaction and surprise. The selection of emotions was based on previous studies of affective states [32] that confirmed the presence of affects during deep learning activities. Also included were two preferences factors: like or dislike of the course content (delivered via lecture). All factors are rated by the surveyed students, using a scale of 1 to 5 for the purposes of our analysis, as shown in Table I .

In a semester, each course has 45 lectures, labeled i=1,. . . ,45. Each course includes theoretical topics as well as applications of theory. The teacher needed a strategy to design the course so that time is split appropriately between theory sections and application sections including prototype demonstrations, project designs, and experiments.

We denote variable T_i and A_i as the time fractions of the ith lecture devoted to theory and applications sections, respectively, for i=1,. . . ,45.

Obviously, $A_i \geq 0$, $T_i \geq 0$, and $A_i + T_i = 1$ for each lecture. We model the two fractions in a linear inequality in the variables T_i and A_i as :

$$A_1 + \cdots + A_i \leq g(T_1 + \cdots + T_i),\ i = 1, \ldots, 45 \qquad (1)$$

where $g(t)$: $R \rightarrow R$ is a given non-decreasing real function to represent the cumulative amount of applications to be covered when the cumulative amount of theory sections covered is t. This function is structured this way because a certain amount of theory has to be covered before application such as examples, simulations and prototype demonstrations can be covered.

The cumulative amount of applications based on covered theory sections can be calculated by

$$g(t) = a(t - b) \qquad (2)$$

where $a, b > 0$, this means that no applications can be covered until b lectures on theory are taught; after that, each theory lecture covered raises the possibility of covering lectures on applications. Based on our past experience, $a = 2$, $b = 1$; this means that 1 theory lecture need to be taught before the first application lecture can be taught. After the theory lecture has been presented, each theory lecture covered raises the possibility of presenting 2 or more lectures on applications. For example, coverage of the continuous-time system theory in the Feedback Control class was followed by two application lectures related to the theory; one on finding an actuator gain for a roll stabilizer on a large ship; the other was on selecting a capacitance value for a simple RC low-pass filter connected in cascade between a magnetic amplifier with low output impedance and a pre-amplifier, for the purpose of meeting specific response requirements.

Students' affect can be significantly dependent on what has just happened in previous class sessions and marginally depend on their incoming beliefs [34]. A student who felt frustrated in previous classes would also keep negative affect in the next class. Those who felt high enjoyment would likely feel highly confident about having learned all the previous material and eager to learn new matter. Affect in future classes can therefore be predicted on the basis of what happened in the most recent class. Variable $\theta \in [0, 1]$ represents the affective volatility of a student. It shows how quickly he or she reacts to the content of recent lectures. If θ is large, the student's future affect is affected relatively little by the affect experienced in the most recent classes. Otherwise, the previous class still has a relatively strong influence on the affective state than the future class does.

The affective evolution model we implemented was based on linear recursion dynamics. A step-wise linear recursion model was used to predict affective states with theory class time T_i as an independent variable. We use the model for short-term class design optimization and the weekly terminal affective state is represented by s_3 because there are 3 classes each week. On a daily basis, we measured student's affective states in every class once every week and set their affects in the next week as an objective function. Each student's long-term terminal affective state is represented as s_{45}. So each student's terminal affect state is calculated by:

$$s_i = (1-\theta)\, s_{i-1} + \theta\,[(\alpha+\mu+\tau)\, T_i + (\beta+\omega+\sigma)\,(1-T_i)] \quad (3)$$

Where $i = 1, \ldots, 45$. $\alpha, \beta, \omega, \sigma, \mu,$ *and* τ shown in Table I, are variables that represent good or bad affects, toward recent lectures, respectively. Notice that s_i is also linear in the same set of variables T_i. Thus, maximizing the objective functions s_i is achieved through a linear program algorithm.

III. RESULTS

Students rated their affective reaction to lectures on a 10-point Likert- type scale (0 = "Not react at all", 0.5 = "normal reaction ", +1 = "immediate reaction"). We measured student's affective states in every class once every week. They rated recent emotions on a 5-point scale (0 = "very negative", 2.5 = "neutral", 5 = "very positive"). Students rated their current affective states on a continuous rating scale from 1 (=" I never experience") to 5 (=" I fully experience") with regard to the following items: boredom, confusion, satisfaction, and surprise.

A. Short-term and long-term course plan

Let's use the Electric Drive class that had 10 students as an example. The students' affective responses are shown in Table II.

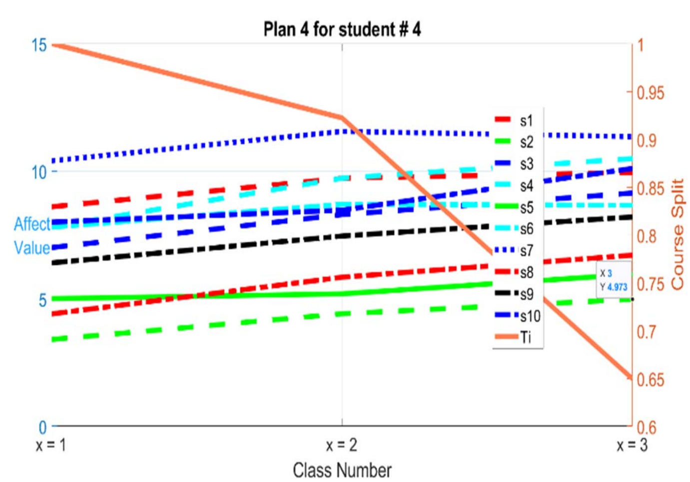
Because some students could respond similarly to the survey questions, a plan that maximized terminal affect of one student may also do so for another student. For example, the student #4 and student #8 needed the same short-term course split plan shown in Fig.2 (a) and (c). But student # 6 needed a different split plan shown in Fig.2 (b) because this student's affective response was different from others. Based on every student's affective response, individual course plans were calculated to maximize every student's affect in a short-term.

TABLE I. AFFECT QUESTIONNAIRE FOR STUDENTS

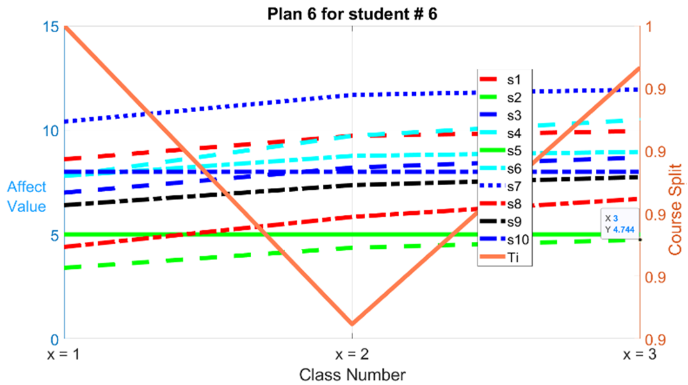
Symbol	Meaning
$\theta \in [0,1]$	How quickly to react to the content of lectures emotionally
$\alpha \in [1,5]$	How much the student likes or dislikes theory
$\beta \in [1,5]$	How much the student likes or dislikes applications
$e \in [1,5]$	The recent experienced affect used as initial value for prediction
$\omega \in [1,5]$	Boredom level to the content of recent theory sections
$\sigma \in [1,5]$	Confusion level to the content of recent theory sections
$\tau \in [1,5]$	Satisfaction level to the content of recent theory sections
$\mu \in [1,5]$	Surprise level to the content of recent theory sections

TABLE II. STUDENT RESPONSES TO AFFECTIVE SURVEY

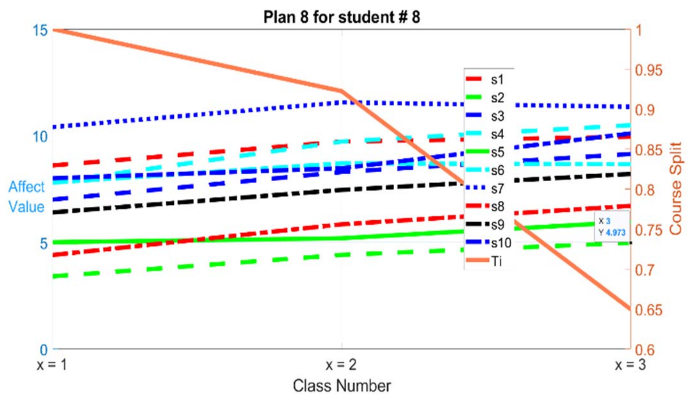
Symbol	ID #1	ID #2	ID #3	ID #4	ID #5	ID #6	ID #7	ID #8	ID #9	ID #10
$\theta \in [0,1]$	0.8	0.6	0.6	0.6	0.4	0.8	0.8	0.4	0.6	1
$\alpha \in [1,5]$	3	1	3	5	1	3	4	4	3	3
$\beta \in [1,5]$	4	2	5	5	1	3	3	4	5	5
$e \in [1,5]$	3	1	4	3	5	3	4	2	4	4
$\omega \in [1,5]$	3	2	3	3	5	3	3	3	3	5
$\sigma \in [1,5]$	3	2	3	3	5	2	4	1	2	4
$\tau \in [1,5]$	4	2	3	3	1	3	4	1	3	3
$\mu \in [1,5]$	3	2	3	3	3	3	4	3	2	2



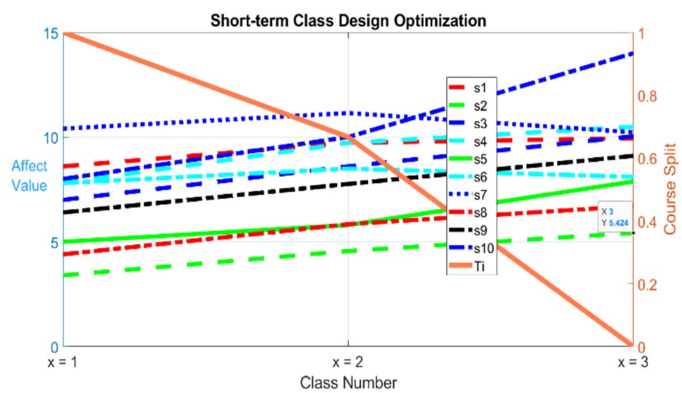
(a)



(b)



(c)



(d)

Fig.2. Course split ratio to maximize students' day to day emotions in each week. The best theory section time fraction Ti in three classes, shown by the decreasing brown curve, and each student's emotional state si, shown by the other curves, versus class sequence number x. For example, (a) The best course split plan for the student #4; (b) The best course split plan for the student #6; (c) The best course split plan for the student #8; (d) The best course split plan to maximize the minimum affect value among students in other plans.

The plan 11 shown in Fig.2 (d) maximized the minimum terminal affect that could be experienced by all 10 students from plan 1 to plan 10. The minimum terminal affect state that is 5.424 in the 11th plan was greater than the minimum values that was 4.744 in the other 10 plans and the maximum affective state calculated by plan 11 was obviously greater than that of the other plans, shown in Fig.2 (d).

Fig.2 shows the plots, for different students, of each lecture's theory time fraction T_i, and different students' emotional state s_i, versus class sequence number x. The students could experience different affects that changes with the changes of the theory and applications time split ranging from 1 (100%) to 0 (0%), shown as T_i in the i_{th} class.

We not only optimized the theory-applications split plan and maximized affective state in each week, but also designed a long-term course plan to maximize the terminal affective states for all 10 students at the end of a semester. First, each plan was designed to maximize the affective state of each student for a long term. For example, plan 3 can cause the student #3 to experience the best affect, as shown in Table III. The affect values in Table III were calculated by our long-term strategy model. Table III lists the 10 students' terminal affective states predicted with 11 different theory-application split plans for 45 classes in a semester. Plans 1 through 10 were designed specifically for student #1 to student #10. Table III shows that each plan, from plan 1 to 10, can help the corresponding student reach his or her best affective state. Therefore, it is reasonable to apply one specific plan only to students that have similar affective responses. It is hard to find one perfect plan to fit all students' need perfectly. We thus apply plan 11 to maximize the minimum terminal affective state among all students in a semester.

TABLE III. PREDICTED LONG-TERM AFFECTIVE STATE OF EACH STUDENT

Student \ plan	ID #1	ID #2	ID #3	ID #4	ID #5	ID #6	ID #7	ID #8	ID #9	ID# 10
Plan 1	**10**	6	10	11	8	9	11	8	9	11
Plan 2	10	**6**	11	11	11	8	10	8	10	14
Plan 3	10	6	**11**	11	11	8	10	8	10	14
Plan 4	10	6	10	**11**	8	9	11	8	9	11
Plan 5	10	6	11	11	**11**	8	10	8	10	14
Plan 6	10	5	9	11	5	**9**	12	8	8	8
Plan 7	10	5	9	11	5	9	**12**	8	8	8
Plan 8	10	6	10	11	8	9	11	**8**	9	11
Plan 9	10	6	11	11	11	8	10	8	**10**	14
Plan 10	10	6	11	11	9	8	10	8	10	**14**
Plan 11	**10**	**6**	**11**	**11**	**11**	*8*	*10*	**8**	**10**	**14**

As seen in Table III, the minimum terminal affect values of all students in the 11th plan are greater than the minimum values in the other plans. Moreover, except student #6 and #7, the other 9 students' terminal affect values in the 11th plan are all maximized when the plan 11 was used. The maximized terminal affect value for each student is highlighted in the fore-mentioned table. Plan 11 maximized the minimum value of the terminal affective state of the student #5. When plan 6 and plan 7 were applied to the students separately, the student #5 had the minimum affect value of 5 among all students but the student's terminal affect value generated by plan 11 was greater than the student's affect values derived from plan #1, #4, #6, #7, #8, #10.

Although this plan cannot help all students attain their own maximum terminal affect values, it can increase the lowest terminal affect value and keep most of the other students get their maximum affect values.

We also considered an alternative plan that could maximize the average affect of all students; however, a higher average affect value might only mean that some students experienced a very negative affect while a larger number of students experienced a positive affect, which implies that the plan could fail students who experienced very negative emotions, which is an outcome not supported by inclusive teaching practices.

In a long-term course design, we took plan #11 into account when we designed the Electric Drive course through a semester. Fig.3 shows that eight students' terminal affect values increased but two students' terminal affect decreased slightly after the theory proportion decreased after the 23rd class.

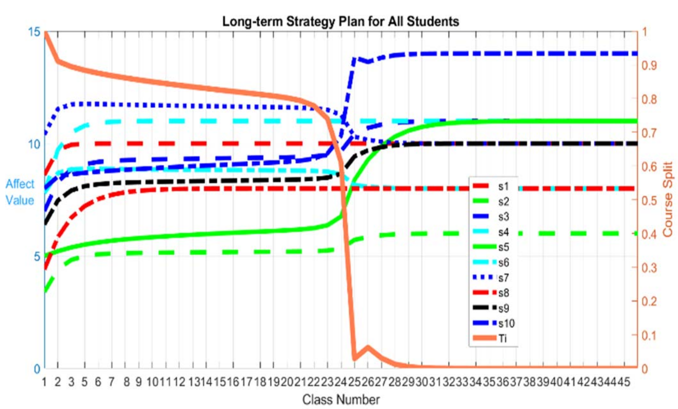


Fig.3. The terminal affective states of each student were affected by the proposed course split ratio in the long-term strategy plan

B. Summary of results

From Fig. 2 and Fig. 3, it is seen that both the short-term optimization model and the long-term strategy model are capable of improving students' affect values by optimally splitting the theory and application section time in each class. Our study not only considered students' affective states when a semester started but also took into account their daily emotions during a learning process to calculate the theory and application time split so as to maximize students' day to day affective state in each week.

In the long-term, the method proposed in this paper can boost students' positive affect, gradually helping all students engage in the course they might otherwise dislike. Because each student's academic background knowledge is different from that of others, some students enjoy learning theoretical materials, including formula derivation and proofs, whereas others dislike such contents, or cannot grasp such knowledge quickly. In most engineering classes, the students expressed an aggregate preference for application. Therefore, in the first twenty classes, we gradually increased the application sections to keep students who disliked theory sections experiencing better affective responses. After the twentieth lesson, the students had learned most theoretical contents and were ready to deepen their understanding of the learned theories by applying them into interesting projects and experiments that boost their emotion values further.

Stephen and Lieven used a similar linear recursion model (referred to as the Boyd model in this paper) to maximize students' affect, but they collected only the students' preference for theory and application lectures before the semester started [35]. Students' feedback at the start of a semester may not reflect their current affective experience along the new course goes with time. Thus, the theory-application split calculated by Boyd model may not be accurate. Our model is clearly more sensitive to the updated affect of students on a week to week basis and can therefore make more precise predictions regarding affective values in both short term and long term course designs.

IV. THE DISCUSSION

This is intended to be a pilot study to test the applicability of a mathematical model that optimizes positive student affect in a classroom. As is appropriate for a feasibility study, the sample size used is small, but this does limit the replicability of the results. More data, from more populations, is needed. There are also persistent construct validity issues inherent in the self-reporting of affective constructs, including personal and academic limitations of the target population, which consists largely of traditionally-aged, male, engineering technology majors who are from the same region where the university is located. As we extend the method beyond the pilot, we intend to amend the survey to include descriptions of each of the affective responses used and provide opportunities for the students to give additional feedback on the applicability of the constructs in the context of the course. Like other previous researchers of affect and learning, we note that mode of instruction is likely a more significant variable than the current model allows. Because the pilot study was limited to a single instructor who utilizes a consistent approach to teaching, we controlled for this in our current design, but any extension of the study beyond a single instructor or instructional modality (in this case, lecture) will need to determine the role of pedagogy, in both the conceptual and mathematical models used.

Although our results are based on a single method of instructional delivery, the purpose of the study is not to endorse any particular pedagogical method. Rather, our findings suggest the significance of *responsiveness* in both the design and delivery of engineering content. The model suggests that as students provide more input about their affective responses to both content and delivery, then the instructor can vary either or both to maximize not only optimum affect but also, by extension, learning [36]. This study did not directly measure learning outcomes, a task for future iterations, but there is considerable indirect evidence of its effectiveness for these courses, including higher averages on course assignments (e.g. project and examinations), and statistically significant increases in student ratings of instruction. These indicators are in keeping with previous studies that have already established strong correlations between cognitive, non-cognitive, and affective outcomes in college-level courses.

Because students vary widely by context, the trade-offs in content and delivery predicted by the model are likely to vary just as widely, but the model serves as a consistent link between student input and optimized outcomes. In the longer run, a dynamic compilation of aggregate student inputs could conceivably be used to make proactive predictions about likely optimization patterns, and therefore inform course design at greater levels of scale and scope, such as on a semester to semester basis, possibly spanning multiple courses or even entire degree programs. Conventional models of learning-centered course (re-)design rely, at least in part, on input from anonymous student evaluations. Emerging course design models emphasize more integral student involvement, often in the form of co-designing roles [37]. We offer a potential third option, in which the role of co-designer is not held by an individual, but rather is crowdsourced across multiple students. In other words, models such as ours suggest the possibilities for how affective teaching and learning could be engineered, or at least could be informed by mathematical models used by engineers, to optimize learning output across increasingly larger numbers of student use cases.

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