A Motivational Thermostat Framework for Enhanced E-Learning Systems

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Abstract
Motivation has never been so important since the learning environment is evolving into a self-centered, distant learning. In this paper, we introduce a motivational thermostat framework, developed based on theoretically grounded pedagogy and motivation tactics from multiple dimensions. Its mechanism maintains learner’s motivational state in between “lose-of-motivation” and “over-motivated”, leading to persistent, lowered attrition rate and more efficient learning. Adaptive Learning Motivational System (ALMOST) is implemented based on the framework. Its effectiveness is evaluated by web-based experiments. The results show that proposed system showed decreased attrition rate and increased learner performance.

1. Introduction

Motivation level of learners is considered the most important factor for efficient and successful learning [30]. “Motivation is not only important because it is a necessary causal factor of learning, but because it mediates learning and is a consequence of learning as well” [25]. Thus relationship between motivation and learning has attracted interest to various researchers approaching from psychology to computational system design perspective during the past decades.

Learner’s motivation is especially important in e-learning systems due to its distinct characteristics compared to offline learning. The teacher or the moderator can directly interact with the learner constantly, both observing the learner’s state and giving an appropriate feedback real-time. However in the e-learning setting, the teacher is not always present. Thereby, it is reported that the learner is easy to lose interest, or sustain his study, resulting increase of attrition rates. There are many other possible reasons for this attrition, but one of the main contributing factor is that the learners are not motivated or cannot sustain their motivation [10, 17].

How motivation and learning interact is still largely understood in the qualitative terms of psychological and educational theory rather than in the details needed for system design due to the complex inherent characteristics of motivation. Motivation research is concrete in its theory. However applying them to e-learning system is not an easy task. Since the e-learning environment is totally different from the offline face-to-face interaction with the teacher, researchers are developing system models, frameworks and design guidelines based on their finding suitable for each types of learning environment. Therefore catching learner’s motivational state and giving an appropriate feedback is important.

We approached motivation in an integrative perspective with achievement motivation. Achievement motivation is a sub-domain of the vast motivation studies which “theorists attempt to explain people’s choice of achievement tasks, persistence on those tasks, vigor in carrying them out, and quality of task engagement”[4] which in turn, influences the learning performance. Specifically, learners are categorized based on their achievement orientation: High in Achievement Motivation (HAM) and Low in Achievement Motivation (LAM) [14] for an adaptive feedback from the system.

A large body of work in motivational e-learning systems takes direct instructional strategies for motivating the learner according to the learner’s motivational state. No study in e-learning has been conducted in consideration of an abnormal motivational state: “over-motivation”. Over-motivation is reported to cause hindrance in learning [22]. Therefore not only motivational strategies are important, but also over-motivated learners are to be supported. Such learners’ achievement orientation is defined and categorized into Extremely High in Achievement Motivation (EHAM), a modified extension from the previous literature [14].

In this paper, we introduce a motivational thermostat framework, developed based on theoretically grounded pedagogy and motivation tactics from multiple dimensions. Our motivational thermostat mechanism maintains the learner’s motivational state in between “lose-of-motivation” and “over-motivated”,
leading to longer persistence, lowered attrition rates, and higher efficiency of learning.

The framework works around four learning processes (see Figure 1) constantly interacting with the motivational thermostat diagnosis module. Across those stages, learner’s quantitative performance and qualitative feedback is collected as an input for diagnostics in real-time. The learner is then categorized into one of the three typical motivational states: EHAM, HAM and LAM. The framework provides a mechanism for controlling learner’s cognitive, emotional state by manipulating influential factors on human’s competitive behavior, leading to increased intrinsic motivation to input more effort. The mechanism is applicable to any e-learning environments where the learners undergo the process of the three critical learning periods defined by Wlodkowski [25].

Theoretical foundation of the framework is described in chapter 3. The framework was further implemented into ALMOST: Adaptive Learning MOtivational SysTem. In chapter 4, the system architecture for ALMOST is further described with each module’s functionality. In the later chapters, the framework and ALMOST is evaluated for its effectiveness with discussions.

2. Related Work

Proposed e-learning framework and system is based on the pedagogy and theories strengthening learner’s motivation. Such research and development is conducted in the domain of motivationally intelligent e-learning system. Bouley et al. [5] defines motivationally intelligent e-learning system as “An intelligent system that is able to deploy resources and tactics dynamically to maintain or increase the student’s desire to learn and her willingness to expend effort in so doing”.

Several researchers in the area of motivationally adaptive computer-assisted instruction (CAI) have raised concerns about how to include adaptive responses to student motivation [6, 24, 28].

Song and Keller [26] designed and evaluated a prototype of motivationally adaptive CAI. They followed the ARCS(Attention, Relevance, Confidence and Satisfaction) model as the foundation of their system. Their focus was to develop and apply motivation sustaining strategies and motivation enhancing strategies into instructions and qualitatively measure increased motivation and its subcategories (effectiveness, continuing motivation and efficiency). Three treatment conditions – motivationally adaptive CAI, motivationally saturated CAI and motivationally minimized CAI – were compared. Their results reveal motivationally adaptive CAI was superior to the other two CAI types for the enhancement of overall motivation and attention. Regarding the other sub-components of motivation, the adaptive use of motivational strategies was partly supported. Therefore it provides evidence supporting that CAI can be designed to be motivationally adaptive to respond to changes in learner motivation that may occur over time.

Woolf et al. [3] integrated pedagogical agents into the testbed tutoring system Wayang Outpost [15] as providers of affective feedback. Learner’s self-reporting strategy was used to take variables relating to affective status as an input for diagnosis. The level of self-concept, confidence, frustration and excitement was measured as the affective criterion. They designed agents to support low achieving students and students with disabilities. The agent termed “Learning Companion” played the role of interacting with the students, mainly by rendering textual responses and gestural animation in the form of a virtual character. The motivating messages were categorized into three types of interventions: attribution, effort-affirmation, and strategic. Their learning agent was quantitatively evaluated by high school students (N=108). Two-third (N=72) received a learning companion and one third (N=36) did not. Results showed that the learning companion enhanced confidence especially for the low-achieving students. Low-achieving students spent more time at posttest time than students with no learning companions, while their counterparts in the no-learning-companion tended to decrease their confidence.

Another line of agent based e-learning system is the AutoTutor [2]. AutoTutor simulates a human tutor by holding a conversation with learner in natural language. Such intelligent e-learning systems give immediate feedback adaptive to the learner’s actions and guide the learner on what to do next. Agent based tutoring system and their theoretical methodologies are well studied in [3, 20, 21, 29].

Recent adaptive intelligent e-learning systems tend to focus more on sensing the learner’s emotion and affect real-time [5, 11, 12]. Sensors are embedded around the learner, including learner’s chair, mouse, monitor, wrist, etc. Posture, movement, grip tension, arousal and facially expressed metal states are captured by such sensors. Captured data is analyzed to provide adaptive feedback to an intelligent tutoring system based on an individual learner’s affective states.

To discuss learner’s emotion, affect and level of motivation, the data collected by sensors may be accurate. However miss-interpretation of the data might occur during the analyzing process.

In the same context, learner’s self-report has been argued for its inaccuracy due to the subjectivity. In the
other hand, self-report methodology is still widely adapted due to its convenience and sufficient accuracy if implemented appropriately. Our approach takes learner’s self-report as an input for emotion and attitude diagnosis.

Majority of the past and current motivationally intelligent e-learning systems are designed and implemented based on the motivation design guidelines [5, 9, 13]. Since the most direct way for a computer system to interact with the learner is by textual instruction, predefined sets of motivational instructions are embedded. At the same time, when and how to render such messages to the learner is modeled.

Our framework and its implement system combine instructional messages as well. Moreover, we take an indirect approach of motivating the learner – by social competition. Since competition is closely related to the motivation in the behavioral science, we focus on the competing behavior and mechanism based e-learning.

3. Motivational Thermostat Framework

Previous works revealed maintaining the learner in the appropriate level of motivation for persistency and learning effort enhancement. The motivational thermostat framework deploys two motivation controlling tactics: adaptive motivational instructions and learner’s manipulated performance visualization. These two tactics were drawn out among previous works which are theoretically grounded as well as systematically quantifiable for system implementation.

Adaptive motivational instructions are well studied and its effectiveness on learner motivation enhancement was validated. Motivational messages provided to LAMs were proven to increase learner motivation. However motivation of HAMs decreased, possibly due to the unnecessary motivational messages given [16]. Therefore the e-learning system requires categorizing the learner into HAM or LAM prior to the learning or during the learning process.

Manipulated performance visualization is based on the competitive behavior mechanism studied in various literatures on social and behavioral sciences. Expectancy-value Theory [18], N-Effect [27] and Process Model of Intrinsic Motivation [19] are considered into the design of framework.

3.1. Theoretical Background

The two main category of theories considered in our study is achievement motivation and competition theories. Those two categories share a common denominator of motivating a learner. First, intrinsic motivation and competition is reviewed for the basic utilization into the proposed framework. Three different forms of motivations identified by Bandura [1]- Attribution Theory, Expectancy-value Theory, and Goal Theory is studied. Lastly, N-Effect is introduced as the theoretical foundation of our motivational thermostat framework.

3.1.1. Intrinsic Motivation and Competition.

Harackiewicz and Sansone proposed a process model that accounts for the effects of contextual and personality factors on intrinsic motivation. The process model shows competition can influence intrinsic motivation in two different ways. It can affect how individuals approach an activity and it can provide informative feedback. Through this model, he validated three hypotheses. First, HAMs enter competitive situations with a stronger desire to achieve competence. Second, HAMs respond to the challenge inherent in competition, become eager and excited, and approach the activity with enthusiasm. Third, HAMs and LAMs respond differently to outcome feedback. For example HAMs may feel especially competent or experience more positive affect after receiving positive feedback in competition, whereas this may not be as true for LAMs.

In Harackiewicz’s findings in 1999, the competitive context affected participants’ orientation (HAM or LAM) to the task. The results suggest compelling evidence that competition has important effects on the way HAMs and LAMs approach a competition, even before feedback is available. He notes competence valuation may be a double-edged sword, however, because it can amplify reactions to negative feedback. Participants who valued competence and received negative feedback demonstrated particularly low levels of positive affect and perceived competence, which in turn reduced subsequent enjoyment.

3.1.2. Attribution Theory.

Attribution theory is concerned with how a learner explains successes and failures. It gives us at least one assumption regarding motivation. Instruction should make an effort to help learners attribute their learning outcomes to the controllable and unstable construct of effort. Learners will have no motivation to participate in a learning experience without the belief that change is possible. Therefore attribution to the on-going learning task in the instruction can be applied to the framework.

3.1.3. Expectancy-value Theory.

Learners expect certain outcomes from behaviors and the more valued the outcomes, the more likely someone is to perform the necessary behavior. Expectancy-value Theory is closely related to competitive behavior, which the
learner decides to put a certain amount of effort by estimating the possibility of meeting a certain needs by doing so.

3.1.4. Goal Theory. Goal theory assumes that establishing goals to be obtained motivates behavior. Goals for learners can be categorized into the performance goal and a learning goal. Performance goal sets a certain performance level that can be measured quantitatively. Learning goal is centered on the learner developing new skills or knowledge. “Performance goals foster the implicit belief that intelligence is fixed, while learning goals associated with the belief that intelligence is malleable and can be developed” [23]. Usually, setting a goal is done before the task, which leads to another strategic consideration of designing instructions in our framework.

3.1.5. N-Effect. N-Effect argues increasing number of competitors in already competitive social settings can decrease learner’s motivation and effort [27]. For example, the individuals trying to finish in the top 20 percent in terms of speed on a time quiz finished significantly faster if they believe they were competing in a pool of 10 versus 100 other people, without compromising accuracy. Since our framework is based on e-learning system, we can manage the number of competitors shown to the learner flexibly so that he can perform at his best.

<table>
<thead>
<tr>
<th>Critical Learning periods</th>
<th>Consideration Factors</th>
<th>Consideration Factors Applied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beginning of the Learning</td>
<td>• Attitudes • Needs</td>
<td>• Provide motivational instructions according to the learner’s emotional state and performance</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Set a reasonable goal for learner by learner performance estimation</td>
</tr>
<tr>
<td>During the Learning</td>
<td>• Stimulation • Affect</td>
<td>not considered</td>
</tr>
<tr>
<td>End of the Learning</td>
<td>• Competence • Reinforcement</td>
<td>• Provide learner’s (manipulated) performance relative to his competitors</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Receive learner’s emotional feedback</td>
</tr>
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</table>

3.2. Framework Design

The Motivational Thermostat Framework is composed of four processes of learning with a module termed Motivational Thermostat Diagnosis in the center (see Figure 1). Design considerations from the Time Continuum Model was applied in three critical learning periods (see Table 1) where motivation is most important [25]: beginning, during and the end of the learning. An additional process of Learner Emotion
Feedback was embedded to receive the emotional state of the learner for analysis. During these four iterative processes of learning, the learner undergoes a dynamic change in motivation. Especially the achievement orientation fluctuates in between HAM and LAM. Maintaining the learner at HAM can derive the best learning performance. Therefore a periodic interaction between the system and the learner is managed through the Motivational Thermostat Diagnosis.

We defined the first step of learning process starts from the “motivationally adaptive instruction” whereas most of the learning material starts with such instructions. Since the system has not acquired learner’s achievement orientation as well as his emotional state, a general version of instruction is given.

The second step of learning process is the actual learning of the material. The only interaction the framework requires is receiving the learning performance (e.g. score, speed, learning time etc). Since the learning material can vary across the domain, no additional instruments for motivation were attached.

The third step is providing the learning results in terms of self-performance, relative ranking and the performance gap between the learner and his peers, or competitors. The special feature of “manipulated performance visualization” is that it does not give an exact performance data and ranking. Instead, a manipulated data is given based on the mechanism based on three motivational theories – Attribution Theory, Expectancy-value Theory and N-Effect. The core of the mechanism is that if the learner’s performance is too low, revealing such result might lead to decrease in learner’s motivation. If the performance is too high, the learner will likely spend less effort in the next round (or set) of learning material since he is already satisfied with the result. It is similar to that of offline learning, where the teacher or the moderator encourages the student by interpreting the low score to be “not bad” instead of “that’s bad”, so that the student will not be disappointed, preventing attrition. It is an indirect way of driving learner’s perception of the competition based learning more positive. The subsequent constructs of motivation including self-efficacy and enjoyment, confidence leads to enhancement of motivation.

Expectancy-value Theory and N-Effect specifically drives the data value of the followings: Number of Competitors (NoC) and Level of Competitors (LoC). NoC and LoC control mechanism will be discussed more in the next chapter.

Finally fourth step which is within the third critical learning period captures learner’s emotional state. Emotions after the learning is captured in this session, either by intelligent sensors or by learner self-report. Diagnosed data categorizes learner into three type of motivational state: HAM, LAM and EHAM (Extremely High in Achievement Motivation). EHAM is a modification of the previous categorization of individuals with high or low achievement motivation. This is the state which the learner is overly motivated that the learning outcomes are abnormal. For example if the learner is overly motivated, his speed in terms of learning performance will increase. However the quality of learning will decrease, as the error rate increases due to the carelessness.

The four processes runs in a cycle. Second and fourth process captures learner’s qualitative data (performance) and qualitative data (emotion feedback). They are diagnosed by the Motivational Thermostat Diagnosis module. First and third process gives the appropriate feedback for enhancing motivation by motivational instructions and ranking feedback adapted to the learner’s motivational status. Note that while going through each cycle, learner’s motivational state and achievement orientation may change due to multiple influential factors. The change may be gradual, or fast, going from EHAM to LAM, vice versa.

4. Adaptive Learning Motivational System

The motivational thermostat framework was implemented into our e-learning system: ALMOST. The system architecture is shown in Figure 2.

The learner interacts with the learning management system (LMS) where the learner consumes the e-learning content just like the conventional one. Since the ALMOST requires a quantitative learner performance for diagnosis, the learning result should be derived as a computable data (e.g. score). The User Performance Manager Module receives the learning result from the LMS and directs to the Diagnosis Manager Module. User Feedback Module retrieves learner’s qualitative data by learner’s self-report of his/her emotional state. The quantitative and qualitative data is then analyzed in the Diagnosis Module. According to the achievement orientation derived, appropriate instructions and ranking status is feedback to the learner by the Instruction and Ranking Manager Modules.

In specific, the mechanism embedded in ALMOST performs diagnosis on user performance and emotional feedback and determines current motivational state in terms of achievement orientation. Considering learner’s state – EHAM, HAM or LAM, system adaptively distributes tailored instructions. Instructions are predefined set of encouragement, praise, and other motivational dialogues defined by previous literatures [3, 7, 26].
After the learning, learner receives a feedback, just like the conventional e-learning system. The difference is that the results are adaptively manipulated by ALMOST. The manipulation algorithm is based on the theories and tactics reviewed in chapter 3. The core is, the performance of the learner remains untouched, while the ranking chart (in comparison to his competitors) is manipulated. This is to drive learner’s perception of his own performance at the level of satisfaction or at the right level of anxiety for higher performance and retention for consistent learning. As described in the previous chapters, competition is a double-edged sword. The right level of stress – namely challenge stress, is known to give a positive impact on motivation to learn, leading to increased learning performance. Therefore maintaining the learner at the level generating challenge stress can positively influence his learning maintaining the state of HAMs.

However the hindrance stress is reached at a certain level of competition anxiety, driving the user into LAMs. The transition between HAMs and LAMs may occur according to the competitive context the system creates. In the case of ALMOST is the manipulation of NoC and LoC of the ranking chart.

5. Evaluation

An experiment was conducted using ALMOST. Boggle, a classic game played using 4x4 alphabet cubes in a total of 16 alphabet letters which players attempt to find words in sequences of adjacent letters. However the experiment subjects were not native English speakers, so the rules were modified that the subjects can combine any letter within the set into words.

From the distributed links to the experiment page, a total of 68 subjects participated in this study. The procedure was instructions provided problem solving, followed by result feedback through the ranking chart. For experimental group, the ranking chart was manipulated each round of boggle. As the analogy of our system ALMOST, the score was maintain at the level where the participant “I almost wanted to give up, but I have to try once more” as the participant commented in the post-experiment study. More specifically, for HAMs, the score was high, but not high in satisfaction. For LAMs, even if the score was low, they were satisfied with it. LAMs, with low ability and motivation, both instructional encouragement and NoC, and LoC was adjusted to provide more relaxing context of competition. Both NoC and LoC was lowered in order to drive the perception of the participant that “I can be in the top 10” if I tried hard enough. For HAMs, NoC was lowered but LoC was increased to provide more competitive context. EHAMS were detected according to the user feedback and performance, which the participant made relatively many errors while motivational state was HAM. After one around, the motivational state was re-diagnosed. No users were allowed to acquire the highest score in the first standing to keep up the motivation. It maintained the learner’s goal of keep on trying to be in the top ranking. However, the participant’s motivational state was reduced, change in state from HAM to LAM. Again,
NoC and LoC were both lowered to increase learner’s achievement motivation.

For controlled group, the ranking chart was not manipulated, and the rankings remained honest. A t-test was conducted to observe the difference between the two groups.

Table 2. Result of t-test

<table>
<thead>
<tr>
<th></th>
<th>t-value</th>
<th>DoF</th>
<th>Sig.</th>
<th>Mean Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>round</td>
<td>-2.605</td>
<td>17.305</td>
<td>.018*</td>
<td>-1.776</td>
</tr>
<tr>
<td>score</td>
<td>-3.678</td>
<td>66</td>
<td>.000**</td>
<td>-1.750</td>
</tr>
</tbody>
</table>

*p<0.05, **p<0.001

A total of 68 samples were collected - 50 samples for controlled group and 18 samples for experimental group. According to the round, the average of controlled group was 1.280 rounds and experimental group was 3.060 rounds. That is 239% more rounds played by the experimental group than the controlled group. The average score of controlled group was 2.610 whereas experimental group was 4.360 shown in Figure 3.

Table 2 shows the result of t-Test. Levene’s test for homogeneity of variance was conducted before t-test. Round ($F=29.712$) rejects the null hypothesis of equal variance however score ($F=2.346$) cannot reject. Thus, score has no problem in equal variance assumption. However, according to the Welch-Satterthwaite formula, the degree of freedom for round was decreased from 66 to 17.305.

Thus, the Table 2 reveals that the round differences between controlled group and experimental group were statistically significant at $p<0.05$ level ($r=2.605$). Moreover, score differences between two groups were statistically significant at $p<0.001$ level ($r=3.678$). Therefore, there is significant evidence on the difference between controlled group and experimental group in terms of round and score.

6. Discussions and Conclusion

We have discussed the importance of motivation and its effect on learner’s performance. The motivational thermostat framework was proposed based on theories relating achievement motivation and competition. Its effectiveness of maintaining learner at an appropriate motivational state, in between “lose-of-motivation” and “over-motivated” was evaluated by the implemented system ALMOST. The framework is flexible over most e-learning system in an instruction-learning-feedback manner. The results revealed that experimental group given the motivational thermostat framework, both the performance and attrition rate was superior to the controlled group’s performance.

It is arguable that the approach of directly manipulating the score and standing may not be so pleasing to the learners when the mechanism is revealed. Also it may reduce or even eliminate the entire effect of the motivational mechanism. However experimental results revealed a positive effect of system’s “white lie” on learners. The motivational thermostat mechanism is effective in generating perceived challenge and increased expectancy value of the challenge outcome. However the challenge stress and hindrance stress caused by a “push to the limit” could exist but was not considered in this study. Our future study will take the challenge and hindrance stress into consideration for minimizing the negative effect and maximizing learner performance and retention in motivational e-learning systems.

7. Acknowledgements

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8. References


