Motivational feedback messages as interventions to frustration in GIFT

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INTRODUCTION

This paper discuss the results of a study ran in September 2015 that examined the effect of motivational feedback messages delivered to participants playing the serious video game vMedic while participants engaged in a modified TC3Sim combat care course delivered by GIFT. Using previously published sensor-free detectors of student frustration (Paquette et al., 2015), GIFT automatically detected whether students were frustrated. In four of five conditions, the system then used the detectors to trigger frustration adaptations The conditions for this study included: (1) control value motivational feedback messages; (2) social identity motivational feedback messages; (3) self-efficiacy motivational messages; (4) non-motivational feedback message condition (control condition 1); (5) no intervention (full control; control condition 2).

THEORY AND PREVIOUS RESEARCH

Effectively supporting cognitive performance is increasingly understood to depend on a broader understanding of the relationship between affect, motivation, and cognition interactions. Prior research in the area of motivation and cognition has demonstrated that the presence of positive motivation enhances working memory, memory encoding, decision making, selective attention, response inhibition, and task switching (Locke & Braver, 2010; Maddox & Markman, 2010; Shohamy & Adcock, 2010). Further, motivational processes associated with affective states have been shown to have had a significant impact on memory, perception, attention, and categorization (Gable & Harmon-Jones, 2010; Harmon-Jones, Gable, & Price, 2013). The purpose of this paper is to discuss the findings of a study run in September 2015 addressing participants' detected frustration via sensor-free affect detectors built into the Generalized Intelligent Tutoring Framework (GIFT) using three distinct motivational manipulations in the form of motivational feedback messages embedded in the combat medical training course TC3Sim/vMedic. We assess the effects of these manipulations on adult learners' learning.

PROJECT DESIGN

The experiment used a modified version of the US Army's TC3Sim course on tactical field care and care under fire, focusing specifically on hemorrhage control and bleeding. Conducted on laptops, the tasks of this experiment included a demographics questionnaire, a pre-test, the modified TC3Sim PowerPoint, five scenarios of vMedic, the Short Grit Scale Survey (Duckworth and Quinn, 2009), a Presence survey (Witmer & Singer, 1994), and a post-test. The data collected in this experiment included all answers to the questionnaires and surveys, and the log files that contained all the data of the experiment and trainee interaction -- including the system detected rates of frustration – that were recorded for each participant. These log files were extracted from GIFT via the Event Report Tool, a function within GIFT that exports all data of all the participants logged onto GIFT while taking the course/experiment.

143 volunteer participants from the Corps of Cadet at the United States Military Academy in West Point, NY participated in this study. The ages of the participants ranged from 17 to 25.

Pre and post test measures were collected for 143 participants. Out of those, 19 participants' log files had a gap in the output where the participant either did not have a pre-test or post-test due to a computer crash and loss of data. Subsequently, these 19 participants were dropped from the data analysis. In total, the final data analysis was run on 124 participants (14 females and 110 males) participated in this study.: (1) 26 participants in the control value motivational feedback messages (condition 1); (2) 26 participants in the social identity motivational feedback messages (condition 2); (3) 24 participants in the self-efficiacy motivational messages (condition 3); (4) 25 participants in the non-motivational feedback message condition (control condition 1); (5) 23 participants in the no intervention (full control; control condition 2).

The main study used a pre- and post-test, control group design. Upon the detection of high frustration, a single audio motivational feedback message would be delivered to the participant by GIFT (except in full control condition 2, which had no messages). The motivational feedback messages were delivered at most once per scenario. This study investigated the effect of three motivational feedback conditions, delivered upon the detection of high frustration.

As such, the design included two control conditions in addition to the three motivational feedback conditions. The two control conditions were: (1) a feedback condition that delivered a non-motivational message upon the initial detection of high frustration; (2) a no message condition where the system would still detect frustration but not deploy any feedback messages. The non-motivational feedback message was simply a factoid related to tourniquets and hemorrhage control.

Students completed five scenarios within vMedic: (1) a relatively easy to solve introductory scenario, (2) multiple injuries; (3) a no-win situation (referred to as Kobayashi-Maru); (4) multiple injuries again; (5) a second no-win situation. These were sequenced in this manner to elicit the most amount of frustration that could be reasonably manipulated without risking complete disengagement from the game.

Message designs

The following messages were designed, recorded, and subsequently delivered as audio clips upon the detection of high frustration. Regardless of how many times a trainee demonstrated frustration in a scenario, the trainee only received a maximum of one message per scenario.

Condition 1: Control-value motivational feedback messages

1. "Studies have shown that between 17%-19% of deaths in Vietnam could have been prevented if tourniquets had been used."

2. "A 2008 study from a hospital in Baghdad found an 87% survival rate with use of tourniquets."

3. "There is no room for hesitation or consultation in facial injuries, and quick action (3-10 minutes) is critical to the survival and recovery of injured soldiers."

4. "The number one cause of preventable deaths in active shooter events is blood loss, and the best way to stop blood loss is to properly apply a tourniquet."

5. “The first U.S. casualty to die in the war from enemy fire was a Special Forces Soldier, SFC Nathan Chapman, who died during medical air-evacuation on 4 January 2002 from isolated limb exsanguination without tourniquet use.”

Condition 2: Social-identity motivational feedback messages

1. “As General Maxwell Thurman said, ‘Make good things happen for our Army.’”

2. “Remember, solder, what General Patton said: ‘An Army is a team. It lives, sleeps, eats, and fights as a team.’”

3. “’Every single man in this Army plays a vital role,’” said General Patton. ‘Don't ever let up. Every man has a job to do and he must do it.’”

4. “General MacArthur once said: ‘Duty, Honor, Country, are three hallowed words that dictate what you ought to be, what you can be, what you will be.’”

5. “General Patton said that the soldier is both a citizen and the Army, and the highest obligation and privilege of citizenship is the bearing arms for one’s country.”

Condition 3: Self-efficacy motivational feedback messages

1. “In this important combat situation, your best outcomes will be achieved if you persist.”

2. “You can succeed in this because you’ve been trained to succeed under all conditions.”

3. “Tell yourself that you will succeed because failure is not an option in this high stakes combat zone.”

4. “Difficult doesn’t mean impossible. It means work harder till your combat mission is achieved.”

5. “In all combat situations, success comes from overcoming the things you thought you couldn’t.”

Control condition 1: Non-motivational feedback messages (each message is associated with a single scenario)

1. “Battlefield care emerged in Europe when Post-Revolutionary France established a system of pre-hospital care that included a corps of litter-bearers to remove wounded individuals from the battlefield.”

2. “The modern combat medic has its roots in the American Civil War, when enlisted soldiers served as hospital stewards.”

3. “As of 10 September 2001, the unreliable, World War II–era U.S. Army tourniquet was the only widely fielded tourniquet in the U.S. military”

4. “In 2003, in the farmlands around Fort Bragg, Amanda Westmoreland became a tourniquet maker by melting and bending plastic tourniquet components in her living rooms, packaging and distributing thousands of assembled tourniquets early in the war against Iraq.”

5. “The use of a tourniquet went from a means of last resort to a means of first aid and became the prehospital medical breakthrough of the wars in Afghanistan and Iraq”

Control Condition 2: (No messages)

Sensor-free detectors

Sensor-free detectors are computational models that automatically detect learners’ affective states from their interaction with online learning. For this September 2015 study, we used the sensor-free affect detector for frustration developed by Paquette and colleagues (2015), built using log data and BROMP field observations from a previous study conducted at West Point (USMA), the same setting as the current study. Machine learning algorithms, implemented in the RapidMiner tool, were then used to identify relationship between features of student interaction and observations of frustration and build a model able to predict when a student was frustrated. The resulting model takes summary features of the student’s behavior as an input and outputs its confidence that the student is frustrated (the confidence is a probability between 0 and 1). For the purpose of this paper’s interventions, we treat a confidence of > 0.5 as evidence that the student is frustrated; values below that are treated as not frustrated.

Results

Analysis of the logs of interventions in vMedic indicated that every student received a feedback message (in conditions with feedback messages), based on the automated detector of frustration, in every vMedic scenario except for the first. This result was not unexpected as the sequence of the vMedic scenarios were designed to have the first scenario be relatively easy to solve.

The condition with the greatest frequency of system-detected frustration was the no message condition, (the full control condition 2), with a mean frequency of 6.70 times that the sensor-free affect detectors detected high frustration. The two conditions with the lowest frequencies detected for high frustration were the control value condition (condition 1), with a mean of 6.19 detected high frustration events, and the self-efficacy condition (condition 3), with a mean of 6.33 detected high frustration events. To examine if there were differences in the frequency of frustration between conditions, a one-way ANOVA analysis was conducted. There was not a statistically significant difference in frustration between conditions, $F(4,119) = .581$, $p = .677$.

To examine if there were differences in the learning gains from pre to post tests between conditions, repeated measures ANOVA analyses. Overall, students did better on the post-test than pre-test: $F(1, 119) = 7.936$, $p = .006$. There was not a significant difference in learning gains by condition in the simplest analysis: $F(4, 119) = .378$, $p = .824$. However, when controlling for frustration ($p=.173$) and 3-way tests-frustration-condition interaction ($p=.011$), condition significantly predicts pre-post test score gain (Repeated measures ANCOVA): $F(4, 114) = 3.680$, $p = .007$.

In examining the motivational conditions (conditions 1, 2, & 3) vs. non-motivational conditions (control conditions 1 & 2), when we control for frustration and a three-way tests-frustration-condition interaction, motivational vs. non-motivational condition significantly predicts pre-post test score gain (Repeated measures ANCOVA): $F(1, 120) = 5.627$, $p = .019$.

Comparing the self-efficacy condition (condition 3) vs. all other conditions, when controlling for frustration and three-way tests-frustration-condition interaction, the self-efficacy condition (condition 3) vs. other conditions significantly predicts pre-post test score gain (Repeated measures ANCOVA): $F(1,120) = 8.853$, $p = .004$. Comparing the control-value condition (condition 1) vs. all other conditions, when controlling for frustration and three-way tests-frustration-condition interaction, the control value theory (condition 1) vs. other conditions does not significantly predict pre-post test score gain (Repeated measures ANCOVA): $F(1, 120) = 1.362$, $p = .246$.

Finally, we examined the relationship between presence and grit, and student learning. Running a repeated measures ANCOVA, presence was not significantly associated with pre-post differences, $F(1,114)= 5.499$, $p = .203$. Grit was not also significantly associated with pre-post test differences by condition, $F(1,114)=2.004$, $p = .160$. However, there was an interaction effect of grit with condition, $F(4,114) = 2.903$, $p = .025$. Grit was significantly associated with pre-post gains within the self-efficacy condition (condition 3), $F(1, 24)=7.304$, $p = .012$. It was not significantly associated with pre-post gains in any other condition.

CONCLUSIONS

In conclusion, this study represents a step in the ongoing effort of developing affect-sensitive feedback interventions to support learner engagement and promote learning gains while engaged in the modified GIFT course for Tactical Combat Casualty Care (TC3). We find that self-efficacy based interventions are associated with better learning, when controlling for frustration, though they do not specifically reduce frustration themselves. This study provides further evidence of the complex interaction of affect, motivation, and cognition. Specifically, this study illuminates the mediating effect that frustration can bring to bear on learning, and provides evidence that through the development of trait-based and situationally grounded motivational messages, connected to an automated detector that infers student frustration, positive learning outcomes can be enhanced in an intelligent tutoring system platform such as GIFT.

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