

# Research Repository

## **Effects of Peers' Emotions on Students' Emotions, Achievement Goals, Mental Effort, and Performance**

Accepted for publication in the Journal of Educational Psychology.

Research Repository link: <https://repository.essex.ac.uk/40068/>

### **Please note:**

Changes made as a result of publishing processes such as copy-editing, formatting and page numbers may not be reflected in this version. For the definitive version of this publication, please refer to the published source. You are advised to consult the published version if you wish to cite this paper.

<https://doi.org/10.1037/edu0000895>.

**Effects of Peers' Emotions on Students' Emotions,  
Achievement Goals, Mental Effort, and Performance**

Yuanyuan Hu<sup>1</sup>, Andrew J. Elliot<sup>2</sup>, Pieter Wouters<sup>1</sup>, Marieke van der Schaaf<sup>3</sup>, Liesbeth Kester<sup>1</sup>,  
and Reinhard Pekrun<sup>4, 5, 6</sup>

<sup>1</sup> Department of Education, Utrecht University

<sup>2</sup> Department of Psychology, University of Rochester

<sup>3</sup> Utrecht Center for Research and Development of Health Professions Education, University  
Medical Center Utrecht, Utrecht, The Netherlands

<sup>4</sup> Department of Psychology, University of Essex

<sup>5</sup> Institute for Positive Psychology and Education, Australian Catholic University

<sup>6</sup> Department of Psychology, University of Munich

Manuscript version accepted for publication. The manuscript may not exactly replicate the  
authoritative document published in the APA journal. It is not the copy of record.

Citation for this article: Hu, Y., Elliot, A. J., Wouters, P., van der Schaaf, M., Kester, L., &  
Pekrun, R. (2024). Effects of peers' emotions on students' emotions, achievement goals, mental  
effort, and performance. *Journal of Educational Psychology, 116* (7), 1283–1299.

<https://doi.org/10.1037/edu0000895>

**Abstract**

Emotion transmission often occurs in social interactions but has attracted limited attention in the education domain. Given the frequent interactions among teachers and students, not only teachers' emotions but also peers' emotions may influence students' learning. This preregistered experimental study investigated how peers' emotions (either enjoyment, neutral state, or frustration) affect students' emotion, motivation, and cognition in observational learning of playing a science game. University students ( $N = 210$ ) watched a video in which a peer model played a game and displayed either enjoyment, a neutral state, or frustration. The data were analyzed by random intercept cross-lagged panel models (RI-CLPMs) with Bayesian estimation and generalized order-restricted information criterion approximation (GORICA). We ran two sets of analyses. In Analysis A, we used the peer emotion display that was intended as the condition variable, excluding participants who perceived a different emotion. In analysis B, we used participants' perception of the peer emotion as the condition variable. Both Analysis A and B revealed that students exposed to peers' enjoyment reported higher enjoyment, relaxation, mastery-approach goals, and game performance, and lower frustration, anger, boredom, and mental effort than those exposed to peers' frustration. We conclude that peers' emotions affect students' achievement emotions, mastery-approach goals, mental effort, and game performance differentially. Educators and researchers should attend to emotion transmission among their students and the role of contagion in education.

*Keywords:* Emotion transmission; achievement emotions; achievement goals; performance; observational learning

**Educational Impact and Implications Statement**

Emotion transmission has primarily been studied in social psychology rather than educational psychology. Our findings suggest that emotion transmission occurs among students: Peers' emotions affect students' motivation, cognitive processes, and performance. The results of this study advance the field of emotion transmission, achievement emotions, achievement goals, instructional design, and particularly, their interconnection.

## 1. Introduction

Emotions play a key role in learning environments as they can help or hinder students' learning (Author, 2006). However, the relations between emotions and learning are not straightforward. For example, enjoyment typically promotes learning, whereas frustration typically undermines learning (Author, 2021). Nonetheless, sometimes enjoyment and frustration do not conform to these expected patterns, as evidenced by research (e.g., Barzilai & Blau, 2014). Enjoyment can hinder learning if it arises from task-irrelevant details that distract attention from the task at hand, while frustration can enhance learning if it strengthens motivation to solve a problem (see also Author, 2020).

According to social contagion theory, emotions can spread among people (i.e., *emotion transmission*; Hatfield et al., 2014). Imagine that a class is discussing a game used to help learning when one student says, *'I really enjoy the game. Can I play more?'*. Another student says, *'I am so frustrated. Can I stop playing?'*. A third student says, *'The game is so-so, nothing in particular.'* How might other students react? Understanding emotion transmission may help us to answer this question and to regulate emotions in learning settings, such as promoting (or avoiding) the transmission of positive (or negative) emotions. However, there is limited research on emotion transmission in the field of education (Burgess et al. 2018). For example, research has shown that teachers can transmit enjoyment to their students (Author, 2018), but to date we are unaware of any experimental studies that have tested emotion transmission from student to student.

Research on emotion design principles in multimedia learning have mainly focused on emotion design features of learning materials that can carry emotions, such as game characters, as well as emotion induction, such as music (Author, 2020; Plass & Hovey, 2021). Teachers' and

students' emotions (Lawson & Mayer, 2022) and their effects on students' learning are also crucial. However, there is a lack of experimental studies testing the effects of peers' emotions on students' learning.

In the present study, we investigate how peers' emotions affect students' emotional, motivational, and cognitive processes and outcomes, as well as their interconnections in observational learning of playing a science game. In the classroom, peers are defined as the students' classmates. Given that this study is the first of this kind, we use a virtual peer that the participants do not know as a starting point. Furthermore, we use observational learning of game playing to represent the broader category of online observational learning.

Moreover, this study uses intensive longitudinal data, measuring variables at multiple time points, to capture the dynamics of emotion, motivation, and cognitive processes as they may change during the course of learning. While most previous studies using intensive longitudinal data to investigate the effects of instructional design features have primarily focused on between-person relations (e.g., Author, 2022a, 2022b), our study takes a different approach. Traditionally, researchers often used the classic cross-lagged panel model (CLPM) to estimate effects over time. However, the CLPM does not separate between- and within-person relations, and the results from between- and within-person relations can diverge substantially (Hamaker et al., 2015). In contrast, our analysis uses the random-intercept cross-lagged panel model (RI-CLPM; Mulder & Hamaker, 2021) to de-confound between- and within-person relations, thereby providing valid evidence of our findings.

### **1.1 Effect of Peers' Emotions and Students' Learning**

Previous research has shown that emotional, motivational, and cognitive processes as well as outcomes interact with each other in learning settings (Author, 2022a, 2022b). To

understand the effects of emotion transmission more fully, it is critical to consider all three types of processes (Schrader et al., 2021). In terms of emotion, achievement emotions are the most relevant in learning settings (Pekrun, 2006). In terms of motivation, achievement goals are crucial motivational constructs for learning (Author, 2001). In terms of cognition, mental effort and cognitive performance are essential constructs (Paas, 1992). Building upon our previous research, which has also shown that these variables interact with each other in game-based learning, this study continues to use and integrate achievement-relevant theories, namely, the control-value theory of achievement emotions (CVT; Author, 2014), achievement goal theory (AGT; Author, 2017), and cognitive load theory (CLT, Sweller et al., 2019).

### *1.1.1 Peers' Emotions and Students' Achievement Emotions*

According to CVT, *achievement emotions* are emotions related to competence-relevant activities, such as attending class, and/or outcomes, that is success or failure, in achievement settings (Author, 2006). Depending on their object, achievement emotions can be distinguished as *activity emotions* related to achievement-relevant activities or task, such as enjoyment, relaxation, frustration, boredom, and anger, and *outcome emotions* related to the outcomes of these activities, such as pride, hope, relief, anxiety, shame, anger, and hopelessness. Moreover, depending on their valence (positive/negative or pleasant/unpleasant) and activation (physiologically activating/deactivating), achievement emotions can be distinguished as *positive activating emotions*, such as enjoyment and pride, *positive deactivating emotions*, such as relaxation and relief, *negative activating emotions*, such as frustration and anxiety, and *negative deactivating emotions*, such as boredom and hopelessness (Author, 2014).

The focus of this study is on activity emotions. Specifically, peers' enjoyment and frustration are selected as the representatives of peers' positive and negative emotions. These

emotions were selected due to their prevalence and relevance in technology-based learning contexts (Author, 2020), differing only in their emotional valence. To establish a reference point for positive and negative emotions, we use *neutral state* - feeling nothing in particular and no preference of one over the other (Gasper et al., 2019).

The phenomenon of people “catching” the emotions of others is often called *emotion transmission* (Author, 2018), emotional contagion (Hatfield et al., 1994), emotional transfer (Parkinson, 2011), emotional crossover (Westman et al., 2013), or emotion diffusion (Peters & Kashima, 2015). In this study, we adopt the most used term, emotion transmission. Three possible mechanisms have been proposed to explain emotion transmission. One mechanism is primitive emotional contagion (Hatfield et al., 2014): The observer may mimic the emotional facial, vocal, and/or postural expressions of the expresser (i.e., *emotional mimicry*) and this mimicry may trigger the same emotional states in the observer (i.e., *afferent feedback*). The second mechanism is emotion categorization (Peters & Kashima, 2015): The observer categorizes the emotional expressions of the expresser as an emotional state (i.e., *categorization*) and this categorization activates the similar emotional state in the observer (i.e., *activation*). The third mechanism is social appraisal (Bruder et al., 2014): The observer may interpret the situation based on information inferred from the emotional expressions of the expresser (i.e., *appraisal*) and this appraisal may trigger the similar emotional state in the observer.

For example, upon witnessing someone else’s smile, one may react in multiple ways: one may mimic the smile in return, may categorize the smile as a feeling of enjoyment, and/or may evaluate the smile as indicating that someone else being happy with the situation. All these responses may trigger one’s own enjoyment. Notably, these three mechanisms – primitive emotional contagion, emotion categorization, and social appraisal – may not be mutually



exclusive of each other, rather, they can coexist and affect the outcomes. Their agreement on the existence of emotion transmission supports our expectation that peers' emotions affect students' achievement emotions, that is, emotion transmission occurs from peers to students (refer to hypotheses **Hemo**).

Emotion transmission can be influenced by various factors, such as activity characteristics, individual differences, and social factors (Fischer & Hess, 2017). Activity characteristics encompass elements like type of activities and perception of the activities. For instance, emotion transmission may be more likely to occur, when activities are collaborative rather than independent in nature. Individual differences encompass elements like the tendency to "catch" others' emotions, game preferences, and different emotional responses to games. For instance, emotion transmission may be more likely to occur, when observers have a strong tendency to be influenced by others' emotions. Social factors encompass elements like perceived likability, ingroup versus outgroup membership, competitive versus cooperative relations, superior and inferior power differences, and desire for affiliation. For instance, emotion transmission may be more likely to occur, when observers like the expresser.

### *1.1.2 Students' Achievement Emotions and Students' Motivation: Reciprocal Effects*

According to AGT, the  $2 \times 2$  achievement goal model (Author, 2017) distinguishes between four achievement goals: 1) *mastery-approach goals*, which is defined as striving for task- or self-based competence, such as learning as much as possible, 2) *mastery-avoidance goals*, which is defined as striving to avoid task-based or self-based incompetence, such as avoiding learning less than one possibly could, 3) *performance-approach goals*, which is defined as striving for other-based competence, such as performing better than others, and 4) *performance-avoidance goals*, which is defined as striving to avoid other-based incompetence,

such as avoiding performing worse than others. This study focuses on all four of these achievement goals as the motivational processes and outcomes.

Regarding the relationship between students' achievement emotions and achievement goals, mastery-based goals mainly focus students' attention on the activity itself, thereby influencing activity emotions, whereas performance-based goals mainly focus students' attention on outcomes, thereby influencing outcome emotions (Author, 2009). Consequently, performance-based goals may be more associated with outcome emotions than activity emotions. Since this study focused only on activity emotions, we expect that peers' emotions affect mastery-based goals but not performance-based goals (refer to hypotheses **Hmot**).

More specifically, mastery-approach goals focus attention on the positive value of the activity and promote feeling in control (Author, 2009). Consequently, mastery-approach goals positively influence positive activity emotions and negatively influence negative activity emotions. Although Author (2009) did not establish a link between mastery-avoidance goals and achievement emotions, we propose that, akin to performance-avoidance goals, the avoidance component makes mastery-avoidance goals focus attention on the negative value of the activity and promote feeling a lack of control. Consequently, mastery-avoidance goals negatively influence positive activity emotions and positively influence negative activity emotions.

While there are no meta-analyses on the relationship between induced achievement emotions and achievement goals, a meta-analysis on personal achievement goals (Huang, 2011) suggests that mastery-approach goals are more strongly associated with positive emotions than negative emotions, whereas mastery-avoidance goals are more strongly associated with negative emotions than positive emotions. Therefore, we expect positive relations between students'

mastery-approach goals and their positive achievement emotions, as well as positive relations between students' mastery-avoidance goals and their negative achievement emotions.

### *1.1.3 Students' Achievement Emotions and Students' Cognition: Reciprocal Effects*

According to CLT, overall cognitive load involves two types: *intrinsic load*, which is defined as load caused by cognitive processes or activities related to learning and performing the task, and *extraneous load*, which is defined as load caused by cognitive processes or activities that are irrelevant for learning and performing the task (Sweller et al., 2019). The overall cognitive load can be estimated by the *mental effort* that students exert on a task (Paas, 1992). This study focuses on mental effort and performance as the cognitive processes and outcomes.

Regarding the relationships between students' achievement emotions, mental effort, and performance, our expectations were guided by three assumptions. The first assumption is related to extraneous load: *The emotions-as-suppressor-of-learning hypothesis* suggests that, based on CLT, positive and negative emotions may impose extraneous load (e.g., via task-irrelevant thinking such as thinking about the consequences of failure; Author, 2003), thereby decreasing performance, compared to a neutral state. The second assumption is based on motivation: *The emotions-as-facilitator-of-learning hypothesis* suggests that positive emotions may increase intrinsic motivation, while negative emotions may increase effort in learning to improve their emotions and extrinsic motivation, both of which increase performance, compared to a neutral state (Plass & Kalyuga, 2019).

The third assumption combines attention and motivation: Based on CVT, positive and negative emotions may have different effects on performance (Author, 2012), as shown in Table 1. As noted above, the present study focuses on activity emotions. Positive activating emotions, such as enjoyment of learning, increase both task attention and

motivation to invest effort, thereby facilitating performance. Conversely, negative deactivating emotions, such as boredom, decrease both task attention and motivation to invest effort, thereby impairing performance.

Moreover, positive deactivating emotions and negative activating emotions have variable effects on performance. Positive deactivating emotions, such as relaxation, broaden the focus, decreasing attention on details while increasing attention on the broad picture. However, they decrease short-term motivation to invest effort while increasing long-term motivation due to reinforcement. Conversely, negative activating emotions, such as frustration or anger, decrease task attention and intrinsic motivation while increasing extrinsic motivation to invest effort in order to avoid failure.

A previous meta-analysis on activity emotions indicated specific relations with performance: a positive association with enjoyment, a negative association with anger and boredom, and a neutral association with frustration (Author, 2021a). Guided by the extraneous load assumption, we therefore expect that students' achievement emotions positively relate to students' mental effort. Furthermore, considering all three assumptions, we expect that students' achievement emotions relate to performance differentially (refer to hypotheses **Hcog**).

#### *1.1.4 Joint Influence of Peers' Emotions and Students' Emotion, Motivation, and Cognition: Reciprocal Effects*

Given that emotions and achievement goals reciprocally influence each other (e.g., Linnenbrink & Pintrich, 2002), instructional design features, such as peers' achievement emotions, may affect students' achievement goals via students' achievement emotions (indirect effects). Specifically, we anticipate that peers' enjoyment positively influences

students' positive emotions and negatively influences students' negative emotions.

Conversely, we anticipate that peers' frustration negatively influences students' positive emotions and positively influences students' negative emotions. Moreover, for both peers' enjoyment and peers' frustration, we anticipate that students' achievement emotions and students' mastery-approach goals or mastery-avoidance goals are linked by reciprocal effects over time, compared with peers' neutral state.

Likewise, given that emotion and cognition reciprocally influence each other over time (Author, 2023), instructional design features, such as peers' achievement emotions, may affect students' mental effort and performance via students' achievement emotions (indirect effects). Specifically, we anticipate that peers' enjoyment positively influences students' positive emotions and negatively influences students' negative emotions, whereas peers' frustration negatively influences students' positive emotions and positively influences students' negative emotions. Moreover, in both cases, we anticipate that students' achievement emotions and students' mental effort or performance are linked by reciprocal effects over time, compared with peers' neutral state.

## **1.2 Present Study**

This study investigates how peers' emotions (enjoyment/frustration/neutral state) affect students' achievement emotions (i.e., positive emotions and negative emotions), achievement goals (i.e., mastery-based and performance-based goals), and cognition (i.e., mental effort and performance). The hypotheses below are broadly stated in terms of positive/negative emotions during observational learning, without delineating specific emotions within these categories. We formulate three different hypotheses for performance based on three different assumptions. We denote 'a' to represent the mean difference in a variable between peers' enjoyment group

(abbreviated as 'e') or peers' frustration group (abbreviated as 'f') and peer's neutral group (i.e., the reference group). For example,  $a_e > 0 > a_f$  means that a variable is larger for peers' enjoyment group than for peers' neutral state group, followed by peers' frustration group.

Students exposed to peers' enjoyment report higher positive achievement emotions (**Hemo1**;  $a_e > 0 > a_f$ ) and lower negative achievement emotions (**Hemo2**;  $a_e < 0 < a_f$ ) than those exposed to peers' neutral state, followed by those exposed to peers' frustration.

Students exposed to peers' enjoyment report higher mastery-approach goals (**Hmot1**;  $a_e > 0 > a_f$ ) and lower mastery-avoidance goals (**Hmot2**;  $a_e < 0 < a_f$ ) than those exposed to peers' neutral state, followed by those exposed to peers' frustration, and students from these three groups report equal performance-approach goals and performance-avoidance goals (**Hmot3**;  $a_e = 0 = a_f$ ).

Students exposed to peers' enjoyment and those exposed to peers' frustration report higher mental effort than those exposed to peers' neutral state (**Hcog1**;  $a_e = a_f > 0$ ).

Students exposed to peers' enjoyment and those exposed to peers' frustration report lower game and posttest performance than those exposed to peers' neutral state (**Hcog2**;  $a_e = a_f < 0$ ); or students exposed to peers' enjoyment and those exposed to peers' frustration report higher game and posttest performance than those exposed to peers' neutral state ( $a_e = a_f > 0$ ); or students exposed to peers' enjoyment report higher game and posttest performance than those exposed to peers' frustration and those exposed to peers' neutral state ( $a_e > 0 = a_f$ ).

## 2. Method

### 2.1 Participants

Participants were recruited through Prolific (<https://www.prolific.co/>) and were offered 10 euros as compensation. The inclusion criteria were English as first language, being an

undergraduate, and majoring in something other than chemical engineering/chemistry, as we used a game about this subject. As suggested by Kline (2015), structural equation modelling needs at least 10 participants per indicator. Given that we had 12 indicators (five from achievement emotions, four from achievement goals, one from mental effort, one from game performance, and one from test performance), our targeted minimum sample size was set at 120. In total, 210 participants were included (100 male, 110 female,  $M = 20.7$  years old,  $SD = 1.4$ ).

## 2.2 Design

We randomly assigned all participants to one of three groups: 1) peers' enjoyment ( $n = 62$ ), 2) peers' frustration ( $n = 33$ ), and 3) peers' neutral state ( $n = 36$ ). This unequal sample distribution was due to the higher number of excluded participants in the peers' frustration and neutral state groups. To facilitate the experiment, we conducted an online experiment designed to create a more controlled learning environment. Conducting experiments on peers' emotion transmission in real classrooms presents challenges, as individual students may express diverse emotions. This diversity makes it difficult to identify effects caused by the experimental manipulation. As such, the online format of the current experiment ensures that students were clearly exposed to either enjoyment, frustration, or a neutral state.

## 2.3 Materials and Measures

All the materials and measures were in English and presented in Qualtrics ([www.qualtrics.com](http://www.qualtrics.com)).

### 2.3.1 The Game – *CosmiClean*

LuGus Studios (<https://www.lugus-studios.be/>) designed *CosmiClean* (<https://recyclegame.eu/>) to teach secondary school and university students the principles of separation processes for recycling materials. Games are a form of play with the characteristics,

such as goals for learning and goals for gameplay (Malone, 1981), rules governing permissible action (Garris et al., 2002), feedback providing timely performance information (Prensky, 2001), or challenges tailored to match player's skill levels (Shute & Ke, 2012).

In CosmiClean, the goal for learning chemistry is to be able to use nine separators, including a sieve, a magnet, a melter, a shredder, a stream separator, a non-ferrous separator, a boiler, a dissolver, and a centrifuge. These separators are employed to separate 12 materials, including iron, plastics, glass, concrete, water, wood, sand, copper, salt, gold, solvent, and fuel. Separation is based on the eight properties, including size, phase, melting point, boiling point, magnetic metal, non-ferrous metal, solubility, and density. The goal for gameplay is that a spaceship crashes and players need to separate materials in order to repair the spaceship. To do so, players enter a series of cargos (i.e., game levels), where they receive a mixture of materials to be separated. The rule is that players need to generate a separation chain, comprising a conveyor for transporting the materials, one or more separators for separating material, and receptors for collecting recycled materials. The materials and separators vary from level to level. The challenge is that as players progress, they become more and more capable and the materials to be separated become more and more complex. Each level lasts approximately 1-5 minutes. The feedback is provided upon submitting a solution in a level; players immediately know if they succeeded. After submission, the materials in this level are collected, without leaderboards or bonus points.

### *2.3.2 Intervention: Videos for Emotion Transmission*

The expressers' emotions can be displayed as dynamic expressions, such as films, or static expressions, such as texts (Herrando & Constantinides, 2021). Dynamic expressions may be more contagious than static expressions (Sato et al., 2008). Meta-analyses also confirm that



film/video clips are an effective method to induce emotions (Fernández-Aguilar et al., 2019; Joseph et al., 2020; Lench et al., 2011), making them recommended standardized stimuli for facilitating emotion transmission (Hatfield et al., 2014).

The intervention materials consisted of three recorded videos, each containing 13 game levels. In the corresponding level of each video, a peer model played the game according to the same script but with different target emotions: enjoyment (link: [here](#)), frustration (link: [here](#)), or neutral state (link: [here](#)). First, the peer model showed the materials to be recycled and the properties of the materials. Then the multiple-answer questions asked participants to choose one, two, or three separators to recycle the materials. These questions were to mimic the real gameplay scenarios, where the player needs to select certain separators to succeed in a game level. Upon answering, they got corrective feedback indicating whether their answer was correct or not. Following the feedback, the peer model explained the correct separators and ran the recycling. We uploaded the videos on Edpuzzle ([www.edpuzzle.com](http://www.edpuzzle.com)). Participants could pause and rewatch but not skip the videos. Each video lasted approximately 23 mins.

The peer model was a male actor in training. He varied his facial, postural, and vocal expressions according to the target emotion. Expressions of enjoyment can be smiles, relaxed faces, open body postures, excited tones, or laughter. Expressions of frustration can be furrowed brows, narrowed eyes, slumped shoulders, restless movements, or sighs. We filmed the videos via first-person perspective (Fiorella et al., 2017). The instructions for watching the videos were: *'You will play the game by watching a video, in which another student will play the game together with you. Please watch the video carefully'*.

### 2.3.3 Achievement Emotions Questionnaire

Given that achievement emotions and achievement goals might decay over time during our one hour-long experiment, we used an experience sampling method (e.g., Author, 2016), with 13 timepoints per person. This approach allowed us to capture the dynamics of emotions and goals. To accommodate time constraints, we used single-item measures, which have been shown to be as reliable as multiple-item measures (Gogol et al., 2014). The achievement emotions questionnaire was based on Author (2016): '*At this moment I am experiencing enjoyment/relaxation/frustration/anger/boredom*' (1 = strongly disagree; 5 = strongly agree). The instructions asked participants to describe their emotions and goals at that moment.

### 2.3.4 Achievement Goals Questionnaire

The achievement goals questionnaire was adopted from the Achievement Goals Questionnaire-Revised (Author, 2008; 1 = strongly disagree, 5 = strongly agree). The items were framed as goals for the game: "*At this moment my goal is to learn as much as possible in the game*" (mastery-approach), "*At this moment my goal is to avoid learning less than I possibly could in the game*" (mastery-avoidance); "*At this moment my goal is to perform better than the other participants*" (performance-approach), and "*At this moment my goal is to avoid performing poorly compared to other participants*" (performance-avoidance).

### 2.3.5 Mental Effort

Paas's (1992) scale was used to measure mental effort: "*How much mental effort did this game level require from you*" (1 = very, very low mental effort; 9 = very, very high mental effort).

### 2.3.6 Game Performance

Game performance was measured by the total number of correct separators that were chosen in the multiple-answer questions in the videos (one question per video).

### 2.3.7 Knowledge Test

The prior and post knowledge test assessed the same chemistry content but with different items. The knowledge tests assessed Remember (5 multiple-choice questions), Apply (5 multiple-choice questions), and Evaluate (3 open-ended questions) based on the Bloom taxonomy (Anderson & Krathwohl, 2001). For example, a Remember question was “*Which processor can separate glass and iron?*”; an Apply question was “*Glass is not metal. Iron, copper, and gold are metal. Which materials can be separated by a non-ferrous separator?*”; and an Evaluate question was “*To separate fuel and copper, your teacher will select either a non-ferrous separator or a dissolver. Explain which one is more proper.*”. The knowledge tests were developed and validated in two studies (Author, 2022a, 2022b), and were reliable (i.e., greatest lower bound: prior knowledge test = .66; post knowledge test = .78). Given that knowledge tests often do not measure the same underlying concept, such as nine separators instead of one in our study, a reliability value lower than .70 is normal (Taber, 2018).

### 2.3.8 Manipulation Check

To avoid interrupting or disturbing the automatic process of emotion transmission, we included a manipulation check on whether participants' perceptions matched the peers' emotions being displayed after the posttest, rather than immediately after watching the videos. Participants chose one of three alternatives to indicate the emotion being displayed: “*The student in the video: a) enjoyed the game, b) was frustrated by the game, c) neither enjoyed nor was frustrated by the game*”.

In the enjoyment condition there were nine participants who perceived a different emotion than the one intended by the condition. In the frustration condition there were 37 such participants, and in the neutral condition there were 33 such participants. Specifically, in the enjoyment condition, five participants perceived peers' enjoyment as a neutral state, while four perceived it as frustration. In the frustration condition, 29 participants perceived peers' frustration as a neutral state, while eight perceived it as enjoyment. In the neutral condition, 25 participants perceived peers' neutral state as enjoyment, while eight perceived it as frustration.

Additionally, we tested whether the included participants ( $n = 131$ ) differed systematically from the excluded participants ( $n = 79$ ) in pretest and demographics measures within each condition. Our analyses revealed that there were no differences in most pretest and demographics measures, except for sex, prior enjoyment, and prior anger (see Supplementary materials for details).

## **2.4 Procedure**

### *2.4.1 Pilot Study*

We ran a small pilot test with 11 participants to check on the fluency and effectiveness of the procedure. This test (descriptively) revealed that the perceptions of most participants matched the displayed peers' emotions, that there were learning gains from the prior to the postgame knowledge test, that the game was neither too difficult nor too easy, and that there were no comprehension or technical problems.

### *2.4.2 Main Study*

After providing informed consent, participants received instruction about the number of sections and their duration. Then they completed the prior knowledge test and reported their achievement goals and achievement emotions (pretest; see Figure 1). They were then randomly

assigned to one of the three experimental conditions and watched the corresponding videos for 30 minutes. After each game level, they reported their achievement emotions, achievement goals, and mental effort. Immediately after watching the full set of videos, they completed the postgame knowledge test (posttest) and the manipulation check.

## **2.5 Scoring, Data Preparation, and Data Analysis**

For the knowledge test, we calculated a sum of correct scores of 10 multiple-choice questions (1 point per question) and three open-ended questions (2 or 4 points per question), resulting in a maximum score of 20 points. For the three open-ended questions, we developed a coding scheme. Two raters scored 10% of the answers for each question independently with very high inter-rater reliability (Cohen's  $k = .836$ ; disagreements resolved through discussion) and then the first author scored the remainder. For game performance, we calculated a sum score of the questions (1, 2 or 3 points per question, maximum: 20 points).

### *2.5.1 RI-CLPMs*

Although our sample size met the minimal requirement, it was relatively modest and led us to adjust our preregistered analysis plan, accordingly. Specifically, we utilized a Bayesian and generalized order-restricted information criterion approximation (GORICA) rather than Null Hypothesis Significance Testing (NHST) approach (see below for further details). The data were analyzed by RI-CLPMs (Mulder & Hamaker, 2021) with the package *blavaan* (Merkle & Rosseel, 2018) in R studio (R Studio Team, 2022) using Bayesian estimation with two Markov chains, and the number of iterations set at 2000. We used RI-CLPMs to accommodate the dynamics of achievement emotions, achievement goals, and mental effort.

In RI-CLPMs, the data were decomposed into a grand mean (i.e., the means over individuals and over time), between-person components (i.e., trait-like, stable deviations from

the grand means) and within-person components (i.e., state-like, temporal deviations from the individual mean; Figure 2). At the between level, we specified random intercepts, which indicate the stable differences between individuals. We added peers' emotions (i.e., enjoyment, frustration, or neutral state) as the grouping variable. Enjoyment, relaxation, frustration, anger, or boredom were included as mediators. Mastery-approach goals, performance-approach goals, mastery-avoidance goals, performance-avoidance goals, mental effort, posttest performance, and game performance were included as outcome variables. Prior enjoyment, prior relaxation, prior frustration, prior anger, prior boredom, prior mastery-approach goals, prior performance-approach goals, prior mastery-avoidance goals, prior performance-avoidance goals, and pretest performance were included as covariates.

At the within level, we specified the autoregression effects and cross-lagged effects. The autoregression effects indicate how the deviations from an individual's mean on one variable at one timepoint predict the deviations from the individual's mean on the same variable at the next timepoint (e.g.,  $Y_t \rightarrow Y_{t+1}$ ). For example, a positive autoregressive effect of enjoyment implies that an individual who experiences deviation from their mean on enjoyment at the current game level is likely to experience deviation from their mean on enjoyment at the next game level (i.e.,  $Enjoyment_t \rightarrow Enjoyment_{t+1}$ ). The cross-lagged effects indicate how the deviations from an individual's mean on one variable at one timepoint predict the deviations from the individual's mean on another variable at the next timepoint (e.g.,  $Y1_t \rightarrow Y2_{t+1}$ ). For example, a positive cross-lagged effect from enjoyment to mental effort implies that an individual who experiences a deviation from their mean on enjoyment at the current game level is likely to experience a deviation from their mean on mental effort at the next game level (i.e.,  $Enjoyment_t \rightarrow Mental\ effort_{t+1}$ ).

We used Bayesian estimation to accommodate small samples (McNeish, 2016). Because we had no prior knowledge about our parameter estimates from previous research, we used default non-informative priors so that priors had little influence on the analysis and parameter estimates were determined solely by the data (Gelman et al., 2014). To make sure that our complex models converged, we used bivariate models with one variable from five achievement emotions and one variable from four achievement goals and mental effort, all of which were measured 13 times during gameplay. In this way, each model included one variable from achievement emotions. This resulted in five RI-CLPM models for each variable and 25 RI-CLPM models in total. The trace plots and Rhats values ( $< 1.01$ ) indicated that our models had good convergence. All the points on the When-to-Worry-and-How-to-Avoid-the-Misuse-of-Bayesian-Statistics checklist (the WAMBS checklist; van de Schoot et al., 2021) were addressed. Missing data were managed by full information maximum likelihood (FIML). The time intervals between consecutive measurement points did not vary.

In evaluating model fit we focused primarily on the comparative fit index (CFI:  $\geq .900$  = acceptable;  $\geq .950$  = excellent), as it is less sensitive to the model and data characteristics than other fit indexes, such as chi-square (Asparouhov & Muthén, 2018; Kenny et al., 2015; Marsh et al., 1988). All our models had acceptable fit, ranging from .900 to .951. We also conducted sensitivity analysis to test the robustness of the models. Specifically, we compared RI-CLPMs with traditional CLPMs (i.e., random-intercepts and covariance between random-intercepts of RI-CLPMs were constrained to zero) and RI-CLPMs with constrained lagged-effects over time (i.e., lagged-effect were constrained as time-invariant). Model comparison was based on the Chi-square ( $\chi^2$ ) difference test. All our models had a better fit than traditional CLPMs and RI-CLPMs with constrained lagged-effects over time.

### 2.5.2 GORICA

For our research question on main effects, we were interested in directly evaluating hypotheses containing inequality constraints (e.g.,  $a_e > 0 > a_f$ ), also called informative hypotheses (Hojtink, 2011). However, the traditional NHST is not appropriate because of its limitations, such as a  $p$ -value cannot quantify the evidence in favor of one hypothesis, NHST cannot test multiple hypotheses simultaneously, and NHST cannot evaluate the hypotheses containing equality (e.g.,  $a_e = a_f$ ) and/or inequality constraints (Altinisik et al., 2021; Wasserstein et al., 2019). To address these limitations, we adopted a newly developed alternative approach called GORICA (Kuiper, 2022; Kuiper et al., 2011). As an extension of Akaike-type information criterion (AIC; Akaike, 1974), GORICA can select the best hypothesis from a set of hypotheses (see Figure S1 in Supplementary Materials).

We used GORICA to evaluate whether our hypothesis of interest has more support than its complement (i.e., all possible hypotheses except the hypothesis of interest). The log likelihood indicates the compatibility of the hypothesis with the data. The values of GORICA and the log likelihood themselves are not interpretable but only comparable. Thus, GORICA weights and log likelihood weights were computed. We calculated the ratio of the GORICA weights (i.e., GORICA weights of hypothesis 1 / GORICA weights of hypothesis 2) and the ratio of log likelihood weights (i.e., log likelihood weights of hypothesis 1 / log likelihood weights of hypothesis 2) for two competing hypotheses. For the hypothesis of interest without equality constraints, if the ratio of GORICA weights exceeds 1 and the ratio of log likelihood weights exceeds 1.5, the hypothesis of interest is more supported than its complement. For the hypothesis of interest with equality constraints, there is no need to check the ratio of log likelihood weights. If our hypothesis of interest lacked support, the best alternative hypothesis was explored.



Because each variable was estimated in five models, if different models supported different hypotheses for the same variable, then the overlapping part of these hypotheses was more supported.

When comparing the hypothesis of interest with its complement, we followed a specific procedure. We first checked the ratio of GORICA weights. If this ratio was not larger than 1, then the hypothesis of interest was not supported, and we explored all possible hypotheses. If this ratio exceeded 1, then we checked the ratio of log likelihood weights. If the ratio of log likelihood weights exceeded 1.5, then the hypothesis of interest was supported. If the ratio of log likelihood weights was not larger than 1.5, then the hypothesis of interest was not supported, and we explored all possible hypotheses. When exploring all possible hypothesis, if one of these possible hypotheses had higher GORICA weights than others, this indicated that there was support for this hypothesis and we further compared this hypothesis with its complement to confirm the support. If two or more hypotheses had higher GORICA weights than others, this indicated that there was support for the overlapping part of these hypotheses and we further compared this overlapping part with its complement to confirm the support.

### *2.5.3 Analysis A and Analysis B*

People may adopt the emotions they perceive in others. Thus, to address the differences between the intended and perceived manipulations, we ran two sets of analyses. In Analysis A, we used the peer emotion display that was intended as the condition variable, excluding participants who perceived a different emotion. In analysis B, we used participants' perception of the peer emotion as the condition variable and added the factor "match" (whether the perceived emotions match the peers' emotions intended in our manipulations) as a predictor. In interpreting our results, we primarily focused on findings that were consistent across both Analysis A and

Analysis B and highlighted the ones that were inconsistent. Additionally, for Analysis A, we tested whether the included participants differed systematically from the excluded participants on outcome measures within each condition. As a sensitivity analysis, we compared the models including the factor “match” as a predictor and the ones excluding it.

## **2.6 Transparency and openness**

We reported all manipulations, all measures, and how we determined the sample size and excluded participants. We follow JARS (Kazak, 2018). The study's design, hypotheses, and analysis plan were preregistered at Open Science Framework (link to be added upon acceptance), where materials and analysis code for this study are available. The study has received approval from the ethics committee of the first author, which complied with APA ethical standards. Data were analyzed using R studio version 2023.04.0-6 (R studio Team, 2022), the package *blavaan*, version 3.2.1 (Merkle & Rosseel, 2018), and the package *restrictor*, version 0.5-30 (Kuiper, 2022).

## **3. Results**

### **3.1 Effects of Peers' Emotions on Students' Learning**

#### *3.1.1 Achievement Emotions*

As shown in Table 2, in both Analysis A and B, students exposed to peers' enjoyment reported higher enjoyment ( $a_e > 0 > a_f$ ) and lower frustration ( $a_e < 0 < a_f$ ) than those exposed to peers' neutral state, followed by those exposed to peers' frustration; students exposed to peers' enjoyment and those exposed to peers' neutral state reported higher relaxation ( $a_e = 0 > a_f$ ) and lower anger ( $a_e = 0 < a_f$ ) than those exposed to peers' frustration; students exposed to peers' enjoyment reported lower boredom than those exposed to peers' neutral state and those exposed to peers' frustration ( $a_e < 0 = a_f$ ).

### 3.1.2 Achievement Goals

In both Analysis A and B, students exposed to peers' enjoyment reported higher mastery-approach goals ( $a_e > 0 = a_f$ ) than those exposed to peers' neutral state and those exposed to peers' frustration; there were no differences in performance-approach goals, and performance-avoidance goals among groups ( $a_e = 0 = a_f$ ). Regarding mastery-avoidance goals, students exposed to peers' enjoyment reported higher mastery-avoidance goals than those exposed to peers' neutral state and those exposed to peers' frustration in Analysis A ( $a_e > 0 = a_f$ ) and there were no differences between groups in Analysis B ( $a_e = 0 = a_f$ ).

### 3.1.3 Mental Effort and Performance

In both Analysis A and B, students exposed to peers' enjoyment and those exposed to peers' neutral state reported lower mental effort ( $a_e = 0 < a_f$ ) and higher game performance ( $a_e > 0 = a_f$ ) than those exposed to peers' frustration. Regarding posttest performance, students exposed to peers' enjoyment reported lower posttest performance than those exposed to peers' neutral state and those exposed to peers' frustration in Analysis A ( $a_e < 0 = a_f$ ) and there were no differences among groups in Analysis B ( $a_e = 0 = a_f$ ).

## 3.2 Within-Person Correlations, Between-Person Correlations, Autoregressive Effects, and Cross-Lagged Effects

As shown in Appendix A, the within-person correlations between positive emotions and mental effort were negative, whereas the within-person correlations between negative emotions and mental effort were positive (average  $r_s$ : Analysis A = -.083 to .182; Analysis B = -.079 to .198). The within-person correlations between positive emotions and achievement goals were positive, whereas the within-person correlations between negative emotions and achievement goals were negative (average  $r_s$ : Analysis A = -.075 to .082; Analysis B = -.064 to .083). Based

on the benchmarks values for interpreting the size of correlations between latent variables (.15, .25, .35 for small, medium, and large effects, respectively; Orth et al., 2022), most within-person correlations were very small in magnitude. This implied that the temporal fluctuations of the variables within persons were not strongly correlated.

The between-person correlations between positive emotions and mental effort or achievement goals were positive ( $r$ : Analysis A = -.023 to .308; Analysis B = .006 to .421) except for the negative between-person correlations between enjoyment and mental effort. The between-person correlations between negative emotions and mental effort or achievement goals were negative ( $r$ : Analysis A = -.405 to .107; Analysis B = -.421 to .110) except for the positive between-person correlations between frustration and mental effort and between performance-avoidance goals and anger or boredom. Most between-person correlations were small to medium in magnitude. This implied that the stable differences of the variables between persons were correlated.

As shown in Appendix B, achievement emotions, mental effort, and achievement goals had autoregressive effects over time (average Bs: Analysis A = .279 to .547; Analysis B = .332 to .610). All autoregressive effects were large. This suggests that the deviations from an individual's mean on the variable at one game level strongly predict the deviations from the individual's mean on the same variable at the next game level.

There were negative cross-lagged effects between positive emotions and mental effort and positive cross-lagged effects between negative emotions and mental effort (average Bs: Analysis A = -.049 to .082; Analysis B = -.069 to .074) except for boredom. There were positive cross-lagged effects between all emotions and mastery-approach goals (average Bs: Analysis A = -.058 to .119; Analysis B = -.027 to .092) except for boredom. There were positive cross-lagged

effects between positive emotions and mastery-avoidance goals and negative cross-lagged effects between negative emotions and mastery-avoidance goals (average Bs: Analysis A =  $-.021$  to  $.168$ ; Analysis B =  $-.084$  to  $.035$ ) except for relaxation, frustration, and anger. There were positive cross-lagged effects between all emotions and performance-approach goals (average Bs: Analysis A =  $.049$  to  $.127$ ; Analysis B =  $-.037$  to  $.127$ ) except for anger. There were positive cross-lagged effects between positive emotions and performance-avoidance goals and negative cross-lagged effects between negative emotions and performance-avoidance goals (average Bs: Analysis A =  $-.088$  to  $.101$ ; Analysis B =  $-.084$  to  $.093$ ). Based on the benchmark values for interpreting the size of cross-lagged effects for RI-CLPMs ( $.03$ ,  $.07$ ,  $.12$  for small, medium, and large effects, respectively; Orth et al., 2022), most cross-lagged effects were small to medium in magnitude. This suggests that the deviations from an individual's mean on one variable at one game level predicted the deviations from the individual's mean on another variable at the next game level.

### 3.3 Analysis A and Analysis B

First, Analysis A and B revealed consistent results for all outcome variables except for mastery-avoidance goals and posttest performance. This shows high convergence. Second, for Analysis A, there were no differences between the included participants and excluded participants within each condition in most outcomes, except for enjoyment, relaxation, boredom, mental effort, and game performance in the enjoyment condition (see Supplementary Materials for details). This suggests that we should exclude participants in Analysis A. Third, for Analysis B, the factor "match" had no statistically significant effects on all outcomes except for posttest performance (Enjoyment and mental effort model:  $B = 1.119$ , 95% Credible Interval =  $[.304, 1.923]$ ; Relaxation and mental effort model:  $B = 1.109$ , 95% Credible Interval =  $[.301, 1.935]$ ;

Frustration and mental effort model:  $B = 1.114$ , 95% Credible Interval =  $[.275, 1.913]$ ; Anger and mental effort model:  $B = 1.123$ , 95% Credible Interval =  $[.321, 1.936]$ ; Boredom and mental effort model:  $B = 1.119$ , 95% Credible Interval =  $[.325, 1.916]$ ). The 'match' participants reported higher posttest performance than the 'mismatch' participants. This suggests that we should include the factor 'match' as a predictor in Analysis B to control for the potential influence of 'match'. Fourth, for the sensitivity analysis of Analysis B, we compared the models including 'match' as a predictor and the ones excluding it (see Table S1, S2, and S3 in Supplementary Materials for details). We found that the main effects of peers' emotions on all outcomes are similar, although the coefficients of the effects slightly changed. This also shows the robustness of the findings in Analysis B.

#### 4. Discussion

Emotion transmission has primarily been studied in social psychology rather than educational psychology. Given the frequent interactions between teachers and students, as well as between students and peers in learning environments, not only teachers' emotions but also peers' emotions may influence students' learning. This research aims to study learning environments that may enhance learning by focusing on emotion transmission among students. We used observational learning of game playing to represent online observational learning environments. To our knowledge, this investigation is the first experimental study to test how peers' emotions affect students' learning in observational learning of game playing. This study is also one of the first in observational learning to focus on how emotion, motivation, cognition, and their interconnection. Moreover, this study is one of the first to decompose within- and between-person relations within the context of an experimental design with intensive longitudinal data (Hamaker et al., 2021).

#### 4.1 Effects of Peers' Emotions on Students' Learning

We found that peers' emotions affected students' achievement emotions, mastery-approach goals, mental effort, and performance, but not performance-based goals. As a whole, students exposed to peers' enjoyment showed higher positive emotions, mastery-approach goals, and game performance, and lower negative emotions and mental effort than those exposed to peers' frustration.

##### 4.1.1 Achievement Emotions

Overall, both Analysis A (using the peer emotion display that was intended as the condition variable) and B (using participants' perception of the peer emotion as the condition variable) revealed that students exposed to peers' enjoyment report higher positive achievement emotions and lower negative achievement emotions than those exposed to peers' frustration. This confirms our hypotheses (**Hemo1** and **Hemo2**). It is congruent with the sparse online research on emotion transmission from teachers to students, which found that students exposed to happy and content instructors reported higher positive emotions (i.e., happy and content) and lower negative emotions (i.e., boredom and frustration) than those exposed to bored and frustrated instructors (e.g., Horovitz & Mayer, 2021; Lawson & Mayer, 2022). These results imply that achievement emotions can be transmitted from peers to students, though the strength of the transmission can vary and may depend on the type of emotion.

##### 4.1.2 Achievement Goals

Overall, both Analysis A and B revealed that students exposed to peers' enjoyment reported higher mastery-approach goals than those exposed to peers' frustration, and students from all three groups reported the same pursuit of performance-approach goals and performance-avoidance goals. This confirms our hypotheses **Hmot1** and **Hmot3**. However, inconsistent with

our hypothesis **Hmot2**, Analysis A revealed that students exposed to peers' enjoyment reported higher mastery-avoidance goals than those exposed to peers' frustration, and Analysis B revealed that students from all three groups reported the same pursuit of mastery-avoidance goals. This inconsistency across Analysis A and B indicates that the findings on mastery-avoidance goals may be not robust and thus, we could not interpret them. These results suggest that peers' activity emotions affect students' mastery-approach goals, but not performance-approach goals, and performance-avoidance goals.

#### *4.1.3 Mental Effort and Performance*

Overall, both Analysis A and B revealed that students exposed to peers' enjoyment showed higher game performance but lower mental effort than those exposed to peers' frustration, and students from all three groups reported the same posttest performance. First, the finding that students exposed to peers' enjoyment showed higher game performance than those exposed to peers' frustration is consistent with our hypothesis (**Hcog2**) and the attention and motivation assumptions supporting the hypothesis. Second, the finding that students exposed to peers' enjoyment reported lower mental effort than those exposed to peers' frustration is inconsistent with our hypothesis (**Hcog1**). One possible explanation for this result is that emotions signify whether task (i.e., game) performance is going well or poorly: Compared with negative emotions, positive emotions are more likely to imply that task performance is already going well (Carver, 2003), suggesting that higher mental effort is not necessary. However, this explanation of the null results is speculative and more empirical work is needed before definitive conclusions regarding these relationships are warranted. Third, inconsistent with our hypothesis **Hcog2**, Analysis A revealed that students exposed to peers' enjoyment reported lower posttest performance than those exposed to peers' frustration, and Analysis B revealed that students from



all three groups reported the same posttest performance. This inconsistency across Analysis A and B indicates that the findings on posttest performance may be not robust and thus, we could not interpret them.

Our results are consistent with research on online emotion transmission from teachers to students, which has found that students exposed to happy and content instructors showed the same immediate posttest performance compared to those exposed to bored and frustrated instructors (Horovitz & Mayer, 2021; Lawson & Mayer, 2022). Our results are also consistent with research on emotion design of learning materials, specifically work finding that positive and negative emotion designs showed the same immediate posttest performance (e.g., Kumar, 2019; Stark et al., 2018). However, our results differ from research on emotion induction, specifically work finding that inducing negative emotions produces higher posttest performance but the same mental effort as compared with inducing positive emotions (e.g., Knörzer et al., 2016). In this work, negative emotions were induced by listening to sad music and recalling sad event, while positive emotions were induced by listening to happy music and recalling happy event. As such, our results suggest that there are differences between the effects of incidental emotions triggered by factors outside the learning task, such as emotion induction, and task-based emotions triggered by the learning task, such as emotion transmission or emotion design of learning material (Author, 2020).

Why should incidental emotions and task-related emotions have different effects? One possible explanation is task attention: According to CVT (Author, 2006), positive incidental emotions, such as enjoyment induced by memories of a positive event, can distract attention from the task. In contrast, positive task-based emotions, such as enjoyment transmitted from

peers' enjoyment, can focus attention on the task. This suggests that positive incidental emotions can decrease performance, whereas positive task-based emotions can increase performance.

#### *4.1.4 Null Results*

Contrary to all our hypotheses on the peers' neutral state group, students exposed to peers' neutral state reported no differences in relaxation, anger, and mental effort compared to those exposed to peers' enjoyment. Similarly, there were no differences in frustration, mastery-approach goals, and game performance compared to those exposed to peers' frustration. These results highlight the complexity surrounding the effects of neutral states on learning.

Previous research has also shown inconsistent evidence in this regard. While a meta-analysis found that compared with neutral designs, positive emotion designs increased mental effort (Wong & Adesope, 2021), another meta-analysis failed to find such an effect (Brom et al., 2018). Moreover, both meta-analyses found that compared with neutral designs, positive emotion designs increased positive emotions, intrinsic motivation, and posttest performance in multimedia learning. However, they also found that effect sizes varied across studies. These inconsistencies suggest that the effect of a neutral design on emotional, motivational, and cognitive outcomes requires further research.

#### **4.4 Limitations**

We acknowledge several limitations of the present research. First, approximately half of our participants in the frustration condition perceived the peer's frustration as a neutral state and approximately half in the neutral state condition perceived the peer's neutral state as enjoyment. There are two possibilities for explaining "failing" the manipulation check. One possibility is that our video stimuli are ambiguous for certain participants. A lack of match between the intended and perceived peer emotion condition may not be an error by the participants, but rather

a normal process involving perception of an ambiguous stimulus. To explore this possibility, we tested whether the included participants differed systematically from the excluded participants on demographic, pretest, and outcome measures within each condition in Analysis A. Our analysis revealed that there were no differences in most demographic measures, pretest variables, and outcomes, with a few exceptions (see Supplementary Materials for details). For sex, we found that 32% of male participants and 43% of female participants did not perceive the male peer's emotions as intended. Female participants seem to be more inclined not to perceive the emotions displayed by the male peer correctly than male participants. This suggests a potential sex-related influence on emotion transmission, with same-sex peers possibly exhibiting stronger emotion transmission than opposite-sex peers. Hence, future research could replicate the study with same-sex peers.

Another possibility is that recognizing enjoyment is simply easier than recognizing frustration or a neutral state. We found that approximately half of our participants in the frustration condition perceived the peer's frustration as a neutral state and approximately half in the neutral state condition perceived the peer's neutral state as enjoyment. This is consistent with research on emotional recognition, which suggests that recognizing positive emotions appears to be easier than recognizing neutral states and negative emotions (e.g., Hugdahl et al., 1993; Nummenmaa & Calvo, 2015). Furthermore, this finding may indicate that transmitting non-positive emotions appears to be more challenging than transmitting positive emotions. This may be because people tend to resist adopting negative emotions and down-regulate them once they occur (Lagattuta & Wellman, 2002), seeking to feel good rather than bad (Larsen, 2000). Future research could include verbal cues, such as sentences expressing emotions (e.g., "I am so frustrated"), to provide clearer indications for frustration and a neutral state.

Second, because we had to exclude many participants, we ended up with a relatively small sample in Analysis A, which necessitated us to use bivariate models when analyzing the data. Future work is needed to replicate the study with a larger sample size. With a larger sample size, it would be possible to incorporate more variables including emotions, achievement goals, mental effort, and performance into one model and accommodate the interactions between them.

Third, emotion transmission can be influenced by various factors, such as activity characteristics, individual differences, and social factors. In the present study, the peer shared similar age and education level with the participants, and they entered the game together. Thus, participants may have perceived him as an ingroup member that was cooperative, which increases the likelihood of contagion. Future research would do well to investigate additional factors, such as varying the match between the model and the perceivers and between their activities.

Fourth, instead of playing the game themselves, participants learned by watching a peer model playing the game. We choose this approach because of practical constraints: The game is very difficult to implement in online experiments. To ensure that participants had a feeling of gameplay and were engaged in learning, we added a multiple-choice question to each game level. The multiple-choice questions asked, "*Which separator(s) can be used to separate materials on this level?*", mimicking the decision-making process in actual gameplay. So, the multiple-choice questions prompt participants to think as if they are playing the game themselves. The participant's activities (i.e., watching the gameplay video) may be somewhat different from the model's activities (i.e., playing the game). However, it remains open as to how the task or activity similarity between the students and peers may impact the degree of emotion

transmission and students' emotions. Future research can test this by replicating the study with a third condition where participants play the game themselves.

#### 4.5 Implications

The present study has several implications for practice and theory. First, our findings suggest that teachers and students would do well to attend to emotion transmission among students and to counteract possible negative effects. This is particularly pertinent in the context of contemporary education, where interpersonal collaboration and communication are increasingly emphasized as essential 21st century competencies (NRC, 2012). We suggest that teachers do so based on different goals of instruction. If the goal is to promote positive emotions and motivation, teachers may guide students to pay attention to their peers' and their own enjoyment. Conversely, if the goal is to promote cognitive performance and an investment of mental effort, teachers may guide students to also pay attention to and use the motivational energy provided by frustration.

Second, students may often express negative emotions in response to various learning activities. Yet, even if this might have negative effects on their peers, employing strategies to downregulate these emotions, such as suppression and concealing them, could also have negative consequences for themselves (Gross, 2015). Educators would do well to encourage students to use proper emotion regulation strategies to downregulate negative emotions, such as situation modification (e.g., change the learning situation to make themselves feel better), attentional deployment (e.g., focus on the present), or cognitive change (e.g., reappraisal: rethink negative emotions as beneficial for learning; Author, 2019).

Third, our findings suggest that instructional design features that primarily target emotions can also affect motivation and cognition. Considering that researchers often focus on

either cognitive, motivational, or emotional theories (Author, 2021), researchers may consider focusing on their interactions and revealing the underlying mechanisms. This including understanding how emotions can best be used to stimulate motivation/cognition or how to recognize emotions that can thwart motivation/cognition and mitigate their influence. Fourth, our findings suggest that higher motivation and positive emotion may not always correlate with higher-quality cognition, despite educators and researchers often aim to design engaging, enjoyable, and effective learning environments.

Fifth, our findings extend recent work on emotion design in multimedia learning, from emotion design of learning materials, emotion induction, and emotion transmission from teachers to students to emotion transmission among students. Sixth, our findings also extend work on social contagion in education, from contagion of intrinsic and extrinsic motivation (Author, 2010) or goals (e.g., Aarts et al., 2004) to emotions. Social contagion theory proposes that most psychological states, such as emotions, motivation, behaviors, values, norms, can be spread among others (Levy & Nail, 1993). Yet, it remains open whether contagion of other psychological states also occurs in education, such as effortful or disruptive behavior, intrinsic or extrinsic values.

## 5. Conclusion

The present study is one of the first to manipulate students' achievement emotions, with a focus on emotional, motivational, and cognitive processes and outcomes. We conclude that peers' emotions may differentially affect students' emotions, achievement Goals, mental effort, and performance in observational learning of game playing. In general, the results of this study advance several domains, including emotion transmission, achievement emotions, achievement goals, instructional design, and particularly, their interconnection.



## References

- Aarts, H., Gollwitzer, P. M., & Hassin, R. R. (2004). Goal contagion: Perceiving is for pursuing. *Journal of Personality and Social Psychology, 87*, 23–37. <https://doi.org/10.1037/0022-3514.87.1.23>
- Anderson, L. W., & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. Longman.
- Altinisik, Y., Van Lissa, C. J., Hoijtink, H., Oldehinkel, A. J., & Kuiper, R. M. (2021). Evaluation of inequality constrained hypotheses using a generalization of the AIC. *Psychological Methods, 26*(5), 599–621. <https://doi.org/10.1037/met0000406>
- Asparouhov, T., & Muthén, B. (2018). *SRMR in Mplus*. Retrieved December 2, 2022, from <https://www.statmodel.com/download/SRMR2.pdf>
- Barzilai, S., & Blau, I. (2014). Scaffolding game-based learning: Impact on learning achievements, perceived learning, and game experiences. *Computers & Education, 70*, 65–79. <https://doi.org/10.1016/j.compedu.2013.08.003>
- Brom, C., Starkova, T., & D'Mello, S. K. (2018). How effective is emotional design? A meta-analysis on facial anthropomorphisms and pleasant colors during multimedia learning. *Educational Research Review, 25*, 100–119. <https://doi.org/10.1016/j.edurev.2018.09.004>
- Bong, M. (2009). Age-Related Differences in Achievement Goal Differentiation. *Journal of Educational Psychology, 101*(4), 879–896. <https://doi.org/10.1037/a0015945>
- Bruder, M., Fischer, A., & Manstead, A. S. (2014). Social appraisal as a cause of collective emotions. In C. von Scheve & M. Salmela (Eds.), *Collective emotions: Perspectives from psychology, philosophy, and sociology* (pp. 141–155). Oxford University Press.
- Burgess, L. G., Riddell, P. M., Fancourt, A., & Murayama, K. (2018). The influence of social



contagion within education: A motivational perspective. *Mind, Brain, and Education*, 12(4), 164–174. <https://doi.org/10.1111/mbe.12178>

Author (2021a).

Carver, C. (2003). Pleasure as a sign you can attend to something else: placing positive feelings within a general model of affect. *Cognition and Emotion*, 17(2), 241–261.

<https://doi.org/10.1080/02699930302294>

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. Harper & Row.

Author (1996).

Author (2017).

Author (2001).

Author (2008).

Fernández-Aguilar, L., Navarro-Bravo, B., Ricarte, J., Ros, L., & Latorre, J. M. (2019). How effective are films in inducing positive and negative emotional states? A meta-analysis. *PloS ONE*, 14(11), e0225040. <https://doi.org/10.1371/journal.pone.0225040>

Fiorella, L., van Gog, T., Hoogerheide, V., & Mayer, R. E. (2017). It's all a matter of perspective: Viewing first-person video modeling examples promotes learning of an assembly task. *Journal of Educational Psychology*, 109(5), 653–665.

<https://doi.org/10.1037/edu0000161>

Fischer, A., & Hess, U. (2017). Mimicking emotions. *Current Opinion in Psychology*, 17, 151–155. <https://doi.org/10.1016/j.copsyc.2017.07.008>

Fredrickson, B. L. (2013). Positive emotions broaden and build. In P. Devine & A. Plant (Eds), *Advances in Experimental Social Psychology* (pp. 1–53). Academic Press.

Author (2018).

Author (2010).

Garris, R., Ahlers, R., & Driskell, J. E. (2002). Games, motivation, and learning: A research and practice model. *Simulation and Gaming, 33*(4), 441–467.

<https://doi.org/10.1177/1046878102238607>

Gasper, K., Spencer, L. A., & Hu, D. (2019). Does neutral affect exist? How challenging three beliefs about neutral affect can advance affective research. *Frontiers in Psychology, 10*, 2476. <https://doi.org/10.3389/fpsyg.2019.02476>

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian data analysis (3<sup>rd</sup> Edition)*. CRC.

Author (2016).

Gogol, K., Brunner, M., Goetz, T., Martin, R., Ugen, S., Fischbach, A., et al. (2014). 'My questionnaire is too long!' the assessments of motivational-affective constructs with three-item and single-item measures. *Contemporary Educational Psychology, 39*, 188e205.

<http://dx.doi.org/10.1016/j.cedpsych.2014.04.002>

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry, 26*(1), 1–26. <http://dx.doi.org/10.1080/1047840X.2014.940781>

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods, 20*(1), 102–116. <https://doi.org/10.1037/a0038889>

Hamaker, E. L., Asparouhov, T., & Muthén, B. (2021). Dynamic structural equation modeling as a combination of time series modeling, multilevel modeling, and structural equation modeling. R. H., Hoyle (Ed.), *The handbook of structural equation modeling* (2<sup>nd</sup> edition, p31). Guilford Press

Author (2019).

- Hatfield, E., Bensman, L., Thornton, P. D., & Rapson, R. L. (2014). New perspectives on emotional contagion: A review of classic and recent research on facial mimicry and contagion. *Interpersona*, 8(2), 159–179. <https://doi.org/10.5964/ijpr.v8i2.162>
- Hatfield, E., Cacioppo, J. T., & Rapson, L. R. (1994). *Emotional Contagion*. Cambridge University Press.
- Herrando, C., & Constantinides, E. (2021). Emotional contagion: a brief overview and future directions. *Frontiers in Psychology*, 12, 712606. <https://doi.org/10.3389/fpsyg.2021.712606>
- Hojtink, H. (2011). *Informative hypotheses: Theory and practice for behavioral and social scientists*. CRC Press.
- Author (2021b).
- Author (2022a).
- Author (2022b).
- Huang, C. (2011). Achievement goals and achievement emotions: A meta-analysis. *Educational Psychology Review*, 23(3), 359–388. <https://doi.org/10.1007/s10648-011-9155-x>
- Hugdahl, K., Iversen, P. M., & Johnsen, B. H. (1993). Laterality for facial expressions: Does the sex of the subjects interact with the sex of the stimulus face? *Cortex*, 29, 325–331.
- Joseph, D. L., Chan, M. Y., Heintzelman, S. J., Tay, L., Diener, E., & Scotney, V. S. (2020). The manipulation of affect: A meta-analysis of affect induction procedures. *Psychological Bulletin*, 146(4), 355–375. <https://doi.org/10.1037/bul0000224>
- Kazak, A. E. (2018). Editorial: Journal article reporting standards. *American Psychologist*, 73(1), 1–2. <https://doi.org/10.1037/amp0000263>
- Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research*, 44(3), 486–507.

<https://doi.org/10.1177/00491241145432>

- Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.
- Knörzer, L., Brünken, R., & Park, B. (2016). Facilitators or suppressors: Effects of experimentally induced emotions on multimedia learning. *Learning and Instruction, 44*, 97–107. <https://doi.org/10.1016/j.learninstruc.2016.04.002>
- Kuiper, R. (2022). AIC-type Theory-Based Model Selection for Structural Equation Models, *Structural Equation Modeling: A Multidisciplinary Journal, 29*(1), 151–158. <https://doi.org/10.1080/10705511.2020.1836967>
- Kuiper, R. M., Hoijsink, H., & Silvapulle, M. J. (2011). An Akaike-type information criterion for model selection under inequality constraints. *Biometrika, 98*, 495–501. <https://doi.org/10.1093/biomet/asr002>
- Kumar, J. A., Muniandy, B., & Wan Yahaya, W. A. J. (2019). Exploring the effects of emotional design and emotional intelligence in multimedia-based learning: an engineering educational perspective. *New Review of Hypermedia and Multimedia, 25*(1-2), 57–86. <https://doi.org/10.1080/13614568.2019.1596169>
- Lagattuta, K. H., & Wellman, H. M. (2002). Differences in early parent-child conversations about negative versus positive emotions: implications for the development of psychological understanding. *Developmental Psychology, 38*(4), 564. <https://doi.org/10.1037/0012-1649.38.4.564>
- Larsen, R. J. (2000). Toward a science of mood regulation. *Psychological Inquiry, 11*(3), 129–141. [https://doi.org/10.1207/S15327965PLI1103\\_01](https://doi.org/10.1207/S15327965PLI1103_01)
- Lawson, A. P., & Mayer, R. E. (2022). Does the Emotional Stance of Human and Virtual

- Teachers in Instructional Videos Affect Learning Processes and Outcomes?. *Contemporary Educational Psychology*, 102080. <https://doi.org/10.1016/j.cedpsych.2022.102080>
- Lench, H. C., Flores, S. A., & Bench, S. W. (2011). Discrete emotions predict changes in cognition, judgment, experience, behavior, and physiology: A meta-analysis of experimental emotion elicitation. *Psychological Bulletin*, 137(5), 834–855. <https://doi.org/10.1037/a0024244>
- Levy, D. A., & Nail, P. R. (1993). Contagion: A theoretical and empirical review and reconceptualization. *Genetic, Social, and General Psychology Monographs*, 119(2), 233–284.
- Linnenbrink, E. A., & Pintrich, P. R. (2002). Achievement goal theory and affect: An asymmetrical bidirectional model. *Educational Psychologist*, 37(2), 69–78. [https://doi.org/10.1207/S15326985EP3702\\_2](https://doi.org/10.1207/S15326985EP3702_2)
- Author (2020).
- Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-fit indexes in confirmatory factor analysis: The effect of sample size. *Psychological Bulletin*, 103(3), 391–410. <https://doi.org/10.1037/0033-2909.103.3.391>
- Author (2003).
- Malone, T. W. (1981). Toward a theory of intrinsically motivating instruction. *Cognitive Science*, 5(4), 333–369. [https://doi.org/10.1016/S0364-0213\(81\)80017-1](https://doi.org/10.1016/S0364-0213(81)80017-1)
- Mayer, R. E. (2019). Computer games in education. *Annual Review of Psychology*, 70, 531–549. <https://doi.org/10.1146/annurev-psych-010418-102744>
- Mayer, R. E. (2021). Cognitive theory of multimedia learning. In R. E. Mayer & L. Fiorella (Eds.), *The Cambridge Handbook of Multimedia Learning* (3<sup>rd</sup> ed., pp. 43–71). Cambridge

university press.

Merkle, E. C., & Rosseel, Y. (2018). blavaan: Bayesian structural equation models via parameter expansion. *Journal of Statistical Software*, 85(4), 1–30.

<https://doi.org/10.48550/arXiv.1511.05604>

Muis, K. R., Ranellucci, J., Trevors, G., & Duffy, M. C. (2015c). The effects of technology-mediated immediate feedback on kindergarten students' attitudes, emotions, engagement and learning outcomes during literacy skills development. *Learning and Instruction*, 38, 1–13. <https://doi.org/10.1016/j.learninstruc.2015.02.001>

Mulder, J. D., & Hamaker, E. L. (2021). Three extensions of the random intercept cross-lagged panel model. *Structural Equation Modeling: A Multidisciplinary Journal*, 28(4), 638–648.

<https://doi.org/10.1080/10705511.2020.1784738>

National Academies of Science, National Research Council (NRC, 2012). Education for Life and Work: Developing Transferable Knowledge and Skills in the 21st Century. *National Academies Press*. <https://doi.org/10.17226/13398>. ISBN 978-0-309-25649-0.

Nummenmaa, L., & Calvo, M. G. (2015). Dissociation between recognition and detection advantage for facial expressions: A meta-analysis. *Emotion*, 15(2), 243–256.

<https://doi.org/10.1037/emo0000042>

Orth, U., Meier, L. L., Bühler, J. L., Dapp, L. C., Krauss, S., Messerli, D., & Robins, R. W. (2022). Effect size guidelines for cross-lagged effects. *Psychological Methods*.

<https://doi.org/10.1037/met0000499>

Paas, F. G. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach. *Journal of Educational Psychology*, 84(4), 429–434.

<https://doi.org/10.1037/0022-0663.84.4.429>

- Park, H.-B., Han, J.-E., & Hyun, J.-S. (2015). You may look unhappy unless you smile: The distinctiveness of a smiling face against faces without an explicit smile. *Acta Psychologica*, 157, 185–194. <https://doi.org/10.1016/j.actpsy.2015.03.003>
- Parkinson, B. (2011). Interpersonal emotion transfer: Contagion and social appraisal. *Social and Personality Psychology Compass*, 5(7), 428–439. <https://doi.org/10.1111/j.1751-9004.2011.00365.x>
- Author (2006).
- Author (2020b).
- Author (2009).
- Author (2012).
- Author (2023).
- Author (2014).
- Peters, K., & Kashima, Y. (2015). A multimodal theory of affect diffusion. *Psychological Bulletin*, 141(5), 966–992. <https://doi.org/10.1037/bul0000020>
- Plass, J. L., & Hovey, C. (2021). The emotional design principle in multimedia learning. In R. E. Mayer & L. Fiorella (Eds.), *The Cambridge Handbook of Multimedia Learning* (3<sup>rd</sup> ed., pp. 324–336). Cambridge University Press.
- Plass, J. L., & Kalyuga, S. (2019). Four ways of considering emotion in cognitive load theory. *Educational Psychology Review*, 31(2), 339–359. <https://doi.org/10.1007/s10648-019-09473-5>
- Plass, J. L., Mayer, R. E., & Homer, B. D. (2020). *Handbook of Game-based Learning*. MIT Press.
- Prensky, M. (2001). *Digital game-based learning*. McGraw-Hill.

- Raaijmakers, S. F., Baars, M., Schaap, L., Paas, F., & Van Gog, T. (2017). Effects of performance feedback valence on perceptions of invested mental effort. *Learning and Instruction*, 51, 36–46. <https://doi.org/10.1016/j.learninstruc.2016.12.002>
- Rollins, L., Bertero, E., & Hunter, L. (2021). Developmental differences in the visual processing of emotionally ambiguous neutral faces based on perceived valence. *PloS ONE*, 16(8), e0256109. <https://doi.org/10.1371/journal.pone.0256109>
- RStudio Team (2022). *RStudio: Integrated Development for R*. RStudio, PBC, Boston, MA URL <http://www.rstudio.com/>
- Salomon, G. (1984). Television is "easy" and print is "tough": The differential investment of mental effort in learning as a function of perceptions and attributions. *Journal of Educational Psychology*, 76(4), 647–658. <https://doi.org/10.1037/0022-0663.76.4.647>
- Sato, W., Fujimura, T., & Suzuki, N. (2008). Enhanced facial EMG activity in response to dynamic facial expressions. *International Journal of Psychophysiology*, 70, 70–74. <https://doi.org/10.1016/j.ijpsycho.2008.06.001>
- Schrader, C., Kalyuga, S., & Plass, J. L. (2021). Motivation and affect in multimedia learning. In R. E. Mayer & L. Fiorella (Eds.), *The Cambridge Handbook of Multimedia Learning* (3<sup>rd</sup> ed., pp. 121–131). Cambridge university press.
- Shute, V. J., & Ke, F. (2012). Games, learning, and assessment. In D. Ifenthaler, et al. (Eds.), *Assessment in game-based learning: foundations, innovations, and perspectives* (pp. 43–58). Springer. [https://doi.org/10.1007/978-1-4614-3546-4\\_4](https://doi.org/10.1007/978-1-4614-3546-4_4)
- Stark, L., Brünken, R., & Park, B. (2018). Emotional text design in multimedia learning: A mixed-methods study using eye tracking. *Computers & Education*, 120, 185–196. <https://doi.org/10.1016/j.compedu.2018.02.003>



- Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*, 31(2), 261–292.  
<https://doi.org/10.1007/s10648-019-09465-5>
- Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48(6), 1273–1296.  
<https://doi.org/10.1007/s11165-016-9602-2>
- van de Schoot, R., Depaoli, S., King, R., Kramer, B., Märtens, K., Tadesse, M. G., ... & Yau, C. (2021). Bayesian statistics and modelling. *Nature Reviews Methods Primers*, 1(1), 1.  
<https://doi.org/10.1038/s43586-021-00017-2>
- Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a world beyond “ $p < 0.05$ ”. *American Statistician*, 73, 1–19. <https://doi.org/10.1080/00031305.2019.1583913>
- Westman, M., Shadach, E., & Keinan, G. (2013). The crossover of positive and negative emotions: The role of state empathy. *International Journal of Stress Management*, 20(2), 116–133. <https://doi.org/10.1037/a0033205>
- Wong, R. M., & Adesope, O. O. (2021). Meta-analysis of emotional designs in multimedia learning: A replication and extension study. *Educational Psychology Review*, 33(2), 357–385. <https://doi.org/10.1007/s10648-020-09545-x>

**Table 1***Effects of activity emotions in short-term tasks (Author, 2012)*

	Example	Task attention and cognitive resources	Motivation to invest effort	Performance
Positive activating	Enjoyment	Increase	Increase	Increase
Positive deactivating	Relaxation	Variable	Variable	Variable
Negative activating	Frustration	Decrease	Variable	Variable
	Anger			
Negative deactivating	Boredom	Decrease	Decrease	Decrease

**Table 2***Main effects of peers' emotions on students' learning after controlling for the covariates*

	Analysis A (N = 131)			Analysis B (N = 210)		
	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc
<i>Enjoyment and mental effort model</i>						
Enjoyment	H: $a_e > 0 > a_f$	1.463	3.504	H: $a_e > 0 > a_f$	1.809	4.155
Mental effort	Ha: $a_e = 0 < a_f$		2.436	Ha: $a_e = 0 < a_f$		2.300
Posttest performance	Ha: $a_e < 0 = a_f$		2.185	Ha: $a_e = 0 = a_f$		4.319
Game performance	H: $a_e > 0 = a_f$		2.717	H: $a_e > 0 = a_f$		2.205
<i>Enjoyment and mastery-approach goals model</i>						
Enjoyment	H: $a_e > 0 > a_f$	1.525	3.739	H: $a_e > 0 > a_f$	2.030	4.682
Mastery-approach goals	Ha: $a_e > 0 = a_f$		2.676	Ha: $a_e > 0 = a_f$		2.425
<i>Enjoyment and mastery-avoidance goals model</i>						
Enjoyment	H: $a_e > 0 > a_f$	1.625	3.878	H: $a_e > 0 > a_f$	3.016	7.000
Mastery-avoidance goals	Ha: $a_e > 0 = a_f$		2.663	Ha: $a_e = 0 = a_f$		4.917
<i>Enjoyment and performance-approach goals model</i>						
Enjoyment	H: $a_e > 0 > a_f$	1.506	3.695	H: $a_e > 0 > a_f$	2.106	4.882
Performance-approach goals	H: $a_e = 0 = a_f$		4.632	Ha: $a_e = 0 = a_f$		5.135
<i>Enjoyment and performance-avoidance goals model</i>						
Enjoyment	H: $a_e > 0 > a_f$	2.021	4.917	H: $a_e > 0 > a_f$	2.185	5.061
Performance-avoidance goals	H: $a_e = 0 = a_f$		4.917	H: $a_e = 0 = a_f$		6.576
<i>Relaxation and mental effort model</i>						
Relaxation	Ha: $a_e = 0 > a_f$		2.448	H: $a_e > 0 > a_f$	1.618	3.408
Mental effort	Ha: $a_e = 0 < a_f$		2.448	Ha: $a_e = 0 < a_f$		2.367
Posttest performance	Ha: $a_e < 0 = a_f$		2.205	Ha: $a_e = 0 = a_f$		4.181
Game performance	H: $a_e > 0 = a_f$		2.717	H: $a_e > 0 = a_f$		2.205
<i>Relaxation and mastery-approach goals model</i>						
Relaxation	Ha: $a_e = 0 > a_f$		2.704	H: $a_e > 0 > a_f$	1.558	4.128
Mastery-approach goals	Ha: $a_e > 0 = a_f$		2.636	Ha: $a_e > 0 = a_f$		2.559

	Analysis A (N = 131)			Analysis B (N = 210)		
	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc
<i>Relaxation and mastery-avoidance goals model</i>						
Relaxation	Ha: $a_e = 0 > a_f$		2.717	Ha: $a_e = 0 > a_f$		2.077
Mastery-avoidance goals	Ha: $a_e > 0 = a_f$		2.704	Ha: $a_e = 0 = a_f$		4.848
<i>Relaxation and performance-approach goals model</i>						
Relaxation	Ha: $a_e = 0 > a_f$		2.690	Ha: $a_e > 0 > a_f$	1.551	3.608
Performance-approach goals	H: $a_e = 0 = a_f$		4.714	Ha: $a_e = 0 = a_f$		5.173
<i>Relaxation and performance-avoidance goals model</i>						
Relaxation	Ha: $a_e = 0 > a_f$		2.717	Ha: $a_e > 0 > a_f$	1.932	4.405
Performance-avoidance goals	H: $a_e = 0 = a_f$		5.024	H: $a_e = 0 = a_f$		7.130
<i>Frustration and mental effort model</i>						
Frustration	H: $a_e < 0 < a_f$	2.802	6.692	H: $a_e < 0 < a_f$	5.623	13.286
Mental effort	Ha: $a_e = 0 < a_f$		2.425	Ha: $a_e = 0 < a_f$		2.401
Posttest performance	Ha: $a_e < 0 = a_f$		2.268	Ha: $a_e = 0 = a_f$		4.319
Game performance	H: $a_e > 0 = a_f$		2.704	H: $a_e > 0 = a_f$		2.195
<i>Frustration and mastery-approach goals model</i>						
Frustration	H: $a_e < 0 < a_f$	2.322	5.711	H: $a_e < 0 < a_f$	6.813	15.949
Mastery-approach goals	Ha: $a_e > 0 = a_f$		2.704	Ha: $a_e > 0 = a_f$		2.559
<i>Frustration and mastery-avoidance goals model</i>						
Frustration	H: $a_e < 0 < a_f$	1.740	4.155	H: $a_e < 0 < a_f$	7.850	18.608
Mastery-avoidance goals	Ha: $a_e > 0 = a_f$		2.717	Ha: $a_e = 0 = a_f$		4.988
<i>Frustration and performance-approach goals model</i>						
Frustration	H: $a_e < 0 < a_f$	2.676	6.634	H: $a_e < 0 < a_f$	11.658	27.571
Performance-approach goals	H: $a_e = 0 = a_f$		5.452	Ha: $a_e = 0 = a_f$		5.289
<i>Frustration and performance-avoidance goals model</i>						
Frustration	H: $a_e < 0 < a_f$	3.651	9.000	H: $a_e < 0 < a_f$	17.182	40.667
Performance-avoidance goals	H: $a_e = 0 = a_f$		5.061	H: $a_e = 0 = a_f$		6.937
<i>Anger and mental effort model</i>						
Anger	Ha: $a_e = 0 < a_f$		2.546	Ha: $a_e = 0 < a_f$		2.460
Mental effort	Ha: $a_e = 0 < a_f$		2.448	Ha: $a_e = 0 < a_f$		2.425

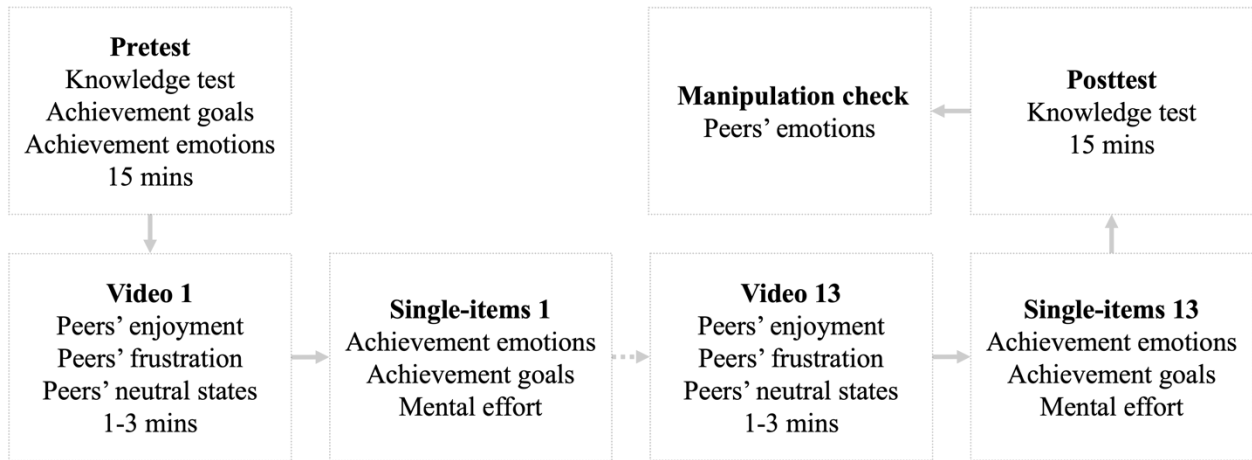
	Analysis A (N = 131)			Analysis B (N = 210)		
	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc
Posttest performance	Ha: $a_e < 0 = a_f$		2.145	Ha: $a_e = 0 = a_f$		4.181
Game performance	H: $a_e > 0 = a_f$		2.717	H: $a_e > 0 = a_f$		2.174
<i>Anger and mastery-approach goals model</i>						
Anger	Ha: $a_e = 0 < a_f$		2.307	Ha: $a_e = 0 < a_f$		2.135
Mastery-approach goals	Ha: $a_e > 0 = a_f$		2.663	Ha: $a_e > 0 = a_f$		2.448
<i>Anger and mastery-avoidance goals model</i>						
Anger	Ha: $a_e = 0 < a_f$		2.413	Ha: $a_e = 0 < a_f$		2.333
Mastery-avoidance goals	Ha: $a_e > 0 = a_f$		2.676	Ha: $a_e = 0 = a_f$		4.917
<i>Anger and performance-approach goals model</i>						
Anger	Ha: $a_e = 0 < a_f$		2.534	Ha: $a_e = 0 < a_f$		2.509
Performance-approach goals	H: $a_e = 0 = a_f$		6.813	H: $a_e = 0 = a_f$		5.494
<i>Anger and performance-avoidance goals model</i>						
Anger	Ha: $a_e = 0 < a_f$		2.497	Ha: $a_e = 0 < a_f$		2.040
Performance-avoidance goals	H: $a_e = 0 = a_f$		5.250	H: $a_e = 0 = a_f$		6.937
<i>Boredom and mental effort model</i>						
Boredom	Ha: $a_e < 0 = a_f$		2.636	Ha: $a_e < 0 = a_f$		2.497
Mental effort	Ha: $a_e = 0 < a_f$		2.484	Ha: $a_e = 0 < a_f$		2.460
Posttest performance	Ha: $a_e < 0 = a_f$		2.195	Ha: $a_e = 0 = a_f$		4.076
Game performance	H: $a_e > 0 = a_f$		2.717	H: $a_e > 0 = a_f$		2174
<i>Boredom and mastery-approach goals model</i>						
Boredom	Ha: $a_e < 0 = a_f$		2.663	Ha: $a_e < 0 = a_f$		2.663
Mastery-approach goals	Ha: $a_e > 0 = a_f$		2.717	Ha: $a_e > 0 = a_f$		2.650
<i>Boredom and mastery-avoidance goals model</i>						
Boredom	Ha: $a_e < 0 = a_f$		2.717	Ha: $a_e < 0 = a_f$		2.546
Mastery-avoidance goals	Ha: $a_e > 0 = a_f$		2.676	Ha: $a_e = 0 = a_f$		5.173
<i>Boredom and performance-approach goals model</i>						
Boredom	Ha: $a_e < 0 = a_f$		2.650	Ha: $a_e < 0 = a_f$		2.690
Performance-approach goals	H: $a_e = 0 = a_f$		4.587	Ha: $a_e = 0 = a_f$		5.369

	Analysis A (N = 131)			Analysis B (N = 210)		
	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc	H or Ha	Loglik. ratio H1/Hc	GORICA. ratio H1/Hc
<i>Boredom and performance-avoidance goals model</i>						
Boredom	Ha: $a_e < 0 = a_f$		2.559	Ha: $a_e < 0 = a_f$		2.703
Performance-avoidance goals	H: $a_e = 0 = a_f$		6.752	H: $a_e = 0 = a_f$		6.092

*Note.* The control group (peers' neutral state) is the reference group;  $a_e$  ( $a_f$ ) represents the mean difference in a variable between the enjoyment (frustration) group and the control group; H = hypothesis of interest; Hc = the complement hypotheses of H or not H; Ha = the best alternative hypothesis when H is not more supported than Hc; loglik = log likelihood; GORICA = generalized order-restricted information criterion approximation; weights = the relative likelihood of a hypothesis given the data and the set of hypotheses; GORICA H/Hc = GORICA weights of H/ GORICA weights of Hc; For example, H of GORICA weights = .718 and Hc of GORICA weights = .282 means that H has  $(.718/.282 = 2.542 > 1$  times) more support than Hc. For the hypothesis of interest with equality restriction, there is no need to check loglik.ratio, so they are not shown.

**Figure 1**

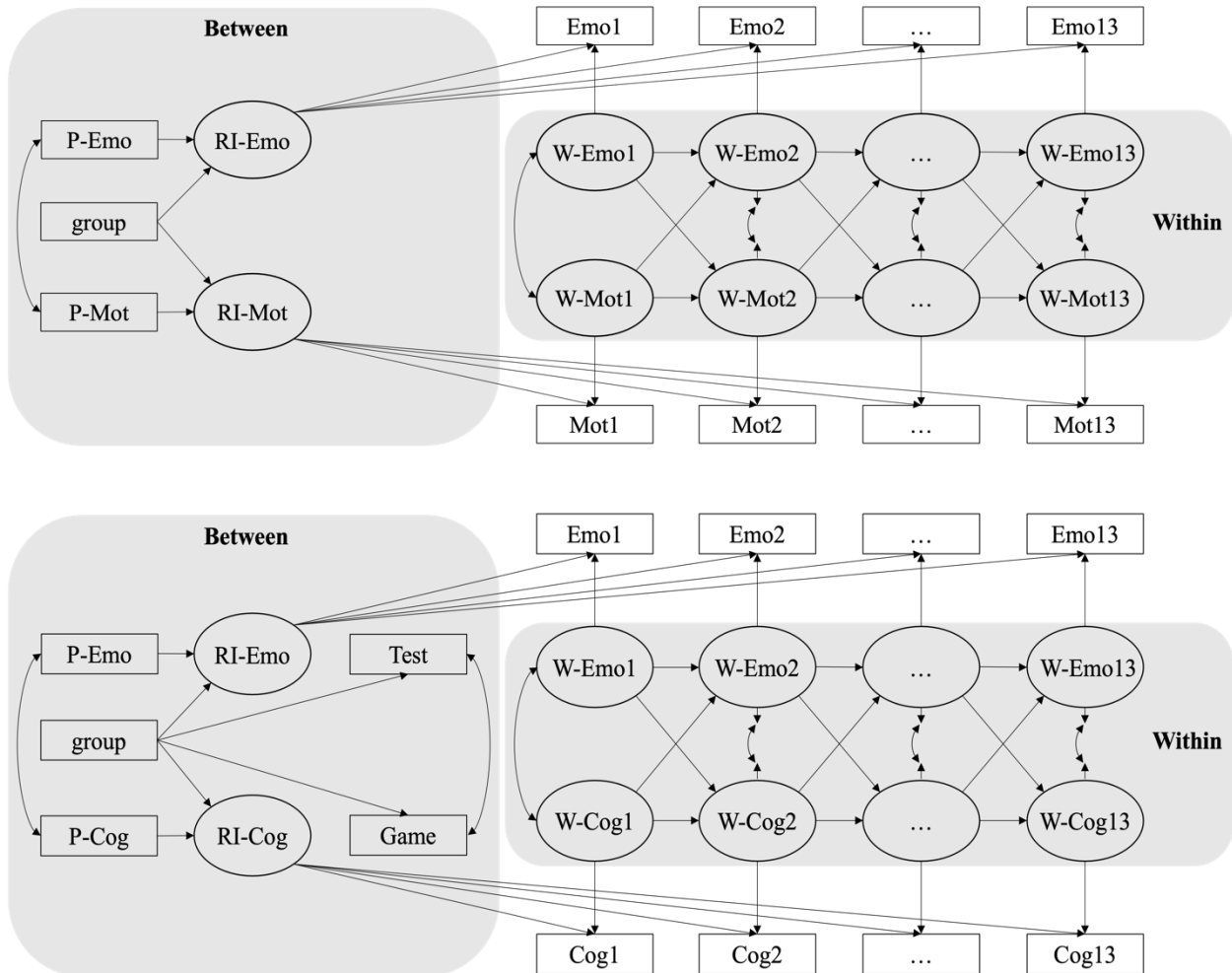
*The procedure and measures*



**Figure 2**

*Random-intercept cross-lagged panel models for achievement emotions and achievement goals*

*(top) and achievement emotions and mental effort (bottom)*



*Note.* Emo = achievement emotions (enjoyment, frustration, boredom, anger, relaxation); Mot = motivation (mastery-approach goals, performance-approach goals, mastery-avoidance goals, performance-avoidance goals); Cog = cognition (mental effort); Test = test performance; Game = game performance; RI-Emo, RI-Mot, RI-Cog = random intercepts for emotion, motivation, and cognition, respectively; P-Emo = prior achievement emotions; P-Mot = prior achievement goals; P-Cog = prior test performance; prior test performance is the covariate of test performance



and game performance, which are not showed due to complexity of the models; W-Emo, W-Mot, W-Cog = within-person emotion, motivation, and cognition, respectively; Numbers indicate number of timepoints; Residual covariances are not shown.

## Appendix A

*Average within-person correlations (correlations between within-person centered variables) and between-person correlations*

*(correlations of random intercepts)*

	Enjoyment	Relaxation	Frustration	Anger	Boredom
<b>Analysis A (N = 131)</b>					
<i>Within-person correlations</i>					
Mental effort	-.072 (.065)	-.083 (.061)	.182 (.086)	.110 (.065)	.015 (.066)
Mastery-approach goals	.075 (.035)	.033 (.030)	-.075 (.043)	-.050 (.032)	-.061 (.034)
Mastery-avoidance goals	.050 (.036)	.015 (.031)	-.021 (.042)	-.007 (.033)	-.034 (.036)
Performance-approach goals	.082 (.037)	.035 (.033)	-.049 (.046)	-.039 (.035)	-.039 (.037)
Performance-avoidance goals	.046 (.034)	.033 (.031)	-.049 (.044)	-.047 (.032)	-.019 (.034)
<i>Between-person correlations</i>					
Mental effort	-.023 (.110)	.100 (.097)	.099 (.104)	-.121 (.106)	-.189 (.128)
Mastery-approach goals	.308 (.073)	.238 (.054)	-.256 (.065)	-.278 (.069)	-.405 (.079)
Mastery-avoidance goals	.199 (.072)	.138 (.055)	-.027 (.059)	-.061 (.056)	-.206 (.079)
Performance-approach goals	.209 (.067)	.193 (.052)	-.120 (.058)	-.174 (.062)	-.210 (.072)
Performance-avoidance goals	.049 (.052)	.157 (.045)	-.022 (.048)	.021 (.044)	.006 (.054)
<b>Analysis B (N = 210)</b>					
<i>Within-person correlations</i>					
Mental effort	-.074 (.054)	-.079 (.048)	.198 (.070)	.119 (.052)	.012 (.054)
Mastery-approach goals	.083 (.028)	.030 (.023)	-.064 (.034)	-.042 (.025)	-.061 (.027)
Mastery-avoidance goals	.046 (.029)	.006 (.025)	-.020 (.036)	-.015 (.028)	-.033 (.029)
Performance-approach goals	.072 (.030)	.027 (.025)	-.039 (.036)	-.031 (.028)	-.031 (.029)
Performance-avoidance goals	.053 (.027)	.029 (.024)	-.039 (.034)	-.041 (.026)	-.028 (.027)
<i>Between-person correlations</i>					
Mental effort	.097 (.094)	.006 (.074)	.102 (.087)	-.110 (.081)	-.178 (.099)
Mastery-approach goals	.421 (.064)	.199 (.044)	-.240 (.052)	-.286 (.053)	-.427 (.066)
Mastery-avoidance goals	.157 (.059)	.120 (.042)	-.042 (.046)	-.027 (.050)	-.007 (.058)
Performance-approach goals	.214 (.057)	.142 (.043)	-.115 (.049)	-.153 (.059)	-.121 (.057)
Performance-avoidance goals	.078 (.050)	.085 (.040)	-.009 (.045)	.008 (.050)	.017 (.049)

## Appendix B

*Average autoregressive effects and average cross-lagged effects*

	Autoregressive effects Emo	Autoregressive effects ME/AG	Cross-lagged effects Emo -> ME/AG	Cross-lagged effects ME/AG -> Emo
<b>Analysis A (N = 131)</b>				
Enjoyment and ME model	.449 (.097)	.365 (.105)	-.006 (.143)	-.024 (.065)
Enjoyment and Map goals model	.445 (.099)	.365 (.107)	.050 (.070)	.119 (.143)
Enjoyment and Mav goals model	.453 (.098)	.279 (.111)	.070 (.072)	.039 (.142)
Enjoyment and Pap goals model	.433 (.099)	.336 (.104)	.084 (.074)	.127 (.129)
Enjoyment and Pav goals model	.444 (.099)	.461 (.106)	.101 (.075)	.078 (.130)
Relaxation and ME model	.351 (.105)	.359 (.108)	-.049 (.171)	-.034 (.058)
Relaxation and Map goals model	.373 (.102)	.378 (.105)	.034 (.082)	.017 (.125)
Relaxation and Mav goals model	.368 (.102)	.303 (.108)	.010 (.085)	-.021 (.130)
Relaxation and Pap goals model	.357 (.103)	.354 (.107)	.049 (.087)	.077 (.119)
Relaxation and Pav goals model	.370 (.098)	.492 (.112)	.103 (.089)	.011 (.112)
Frustration and ME model	.321 (.100)	.363 (.105)	.046 (.116)	.041 (.087)
Frustration and Map goals model	.326 (.099)	.372 (.101)	.000 (.055)	.004 (.178)
Frustration and Mav goals model	.396 (.115)	.363 (.111)	-.018 (.053)	.053 (.182)
Frustration and Pap goals model	.346 (.099)	.352 (.106)	-.028 (.057)	-.024 (.170)
Frustration and Pav goals model	.348 (.098)	.499 (.107)	-.071 (.058)	-.075 (.165)
Anger and ME model	.511 (.112)	.359 (.107)	.082 (.154)	.055 (.063)
Anger and Map goals model	.536 (.100)	.366 (.106)	.030 (.077)	.083 (.137)
Anger and Mav goals model	.532 (.102)	.516 (.162)	-.014 (.081)	.168 (.150)
Anger and Pap goals model	.595 (.105)	.359 (.112)	.009 (.083)	.108 (.126)
Anger and Pav goals model	.555 (.103)	.507 (.105)	-.088 (.078)	-.050 (.124)
Boredom and ME model	.525 (.096)	.368 (.107)	.048 (.146)	-.011 (.063)
Boredom and Map goals model	.566 (.095)	.351 (.105)	-.043 (.066)	-.058 (.140)
Boredom and Mav goals model	.532 (.096)	.294 (.111)	-.019 (.072)	-.017 (.135)
Boredom and Pap goals model	.563 (.092)	.353 (.102)	-.033 (.070)	-.037 (.125)
Boredom and Pav goals model	.548 (.093)	.506 (.113)	-.063 (.074)	-.087 (.130)

	Autoregressive effects Emo	Autoregressive effects ME/AG	Cross-lagged effects Emo -> ME/AG	Cross-lagged effects ME/AG -> Emo
<b>Analysis B (N = 210)</b>				
Enjoyment and ME model	.430 (.077)	.351 (.087)	-.014 (.115)	-.027 (.049)
Enjoyment and Map goals model	.418 (.078)	.345 (.081)	.046 (.055)	.086 (.109)
Enjoyment and Mav goals model	.431 (.078)	.428 (.088)	.034 (.060)	.035 (.101)
Enjoyment and Pap goals model	.426 (.078)	.378 (.084)	.080 (.060)	.087 (.099)
Enjoyment and Pav goals model	.436 (.078)	.478 (.085)	.064 (.060)	.093 (.103)
Relaxation and ME model	.332 (.083)	.343 (.083)	-.069 (.132)	-.031 (.046)
Relaxation and Map goals model	.342 (.082)	.357 (.081)	.019 (.065)	-.011 (.100)
Relaxation and Mav goals model	.340 (.081)	.438 (.085)	-.003 (.071)	.007 (.087)
Relaxation and Pap goals model	.335 (.081)	.386 (.083)	.027 (.070)	.052 (.090)
Relaxation and Pav goals model	.341 (.081)	.488 (.087)	.047 (.070)	.030 (.088)
Frustration and ME model	.349 (.077)	.352 (.085)	.005 (.088)	.007 (.067)
Frustration and Map goals model	.342 (.076)	.360 (.079)	-.006 (.042)	.033 (.141)
Frustration and Mav goals model	.351 (.075)	.440 (.095)	-.018 (.045)	.006 (.129)
Frustration and Pap goals model	.354 (.076)	.385 (.082)	-.024 (.044)	-.004 (.127)
Frustration and Pav goals model	.361 (.075)	.487 (.086)	-.048 (.044)	-.065 (.129)
Anger and ME model	.465 (.081)	.341 (.084)	.074 (.118)	.045 (.049)
Anger and Map goals model	.456 (.078)	.362 (.080)	.022 (.058)	.092 (.103)
Anger and Mav goals model	.474 (.079)	.434 (.094)	-.032 (.064)	.021 (.098)
Anger and Pap goals model	.447 (.083)	.382 (.087)	-.017 (.065)	.041 (.098)
Anger and Pav goals model	.478 (.079)	.494 (.088)	-.084 (.063)	-.064 (.099)
Boredom and ME model	.560 (.076)	.350 (.086)	.050 (.108)	-.005 (.049)
Boredom and Map goals model	.564 (.074)	.349 (.082)	-.027 (.053)	-.027 (.109)
Boredom and Mav goals model	.610 (.071)	.441 (.093)	-.064 (.056)	-.084 (.099)
Boredom and Pap goals model	.603 (.073)	.397 (.080)	-.032 (.055)	-.039 (.096)
Boredom and Pav goals model	.602 (.072)	.497 (.088)	-.059 (.056)	-.071 (.100)

*Note.* Emo = Emotions; ME = mental effort; AG = achievement goals; Map = mastery-approach; Pap = performance-approach; Mav =

mastery-avoidance; Pav = performance-avoidance.