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Sachisthal, M.S.M.; Raijmakers, M.E.J.; Jansen, B.R.J.

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Trait and state math EAP (emotion, appraisals and performance) profiles of Dutch teenagers

Maien S.M. Sachisthal [a,*], Maartje E.J. Raijmakers [a,b], Brenda R.J. Jansen [a]

[a] Department of Psychology, University of Amsterdam, 1018 WT Amsterdam, the Netherlands
[b] Educational Studies & Learn!, Free University, 1081 BT Amsterdam, the Netherlands

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ABSTRACT

The current study investigated emotion appraisal performance (EAP) profiles – which may occur due to the strong relation between these constructs – of Dutch teenagers ($N = 384$; mean age = 12.88) from upper secondary school. The EAP profiles included emotions, appraisals and performance on two levels of conceptualization: a more stable trait-level and an activity-related state-level. We used a model-based latent profile analysis to identify the mathematics-EAP profiles. On the trait level, two profiles emerged: a moderate profile and a maladaptive EAP profile. On the state level, across two different math task conditions, four learning profiles emerged: an adaptive profile, a moderate profile, a negative emotion, lower appraisals profile, and a bored, low value, slow EAP profile. Profile membership across levels was related, but not perfectly: Learners in the moderate trait learning profile were most likely in either the adaptive or the moderate state profile. Results of the person-centered analyses provide an indication of how the pattern of associations of appraisals, emotions and achievement may result in different learning profiles and how they relate across learning contexts.

Math performance does not come in isolation: It results from the level of effort exercised by a learner who appraises the math activity and its success/failure outcomes, and who experiences emotions around the activity, according to the Control-Value theory of achievement emotions (CV-theory; Pekrun, 2006; Pekrun et al., 2017). As emotions, appraisals are in turn affected by performance (Ahmed et al., 2012; Arens et al., 2017; Hagenauer & Hascher, 2014; Luo et al., 2011; Ma & Xu, 2004; Meece et al., 1990; Pekrun, 1992; Pekrun et al., 2014, 2017; Putwain et al., 2018; Saw & Chang, 2018; Sutter-Brandenberger et al., 2018), it is highly probable that learners will show qualitatively different emotion, appraisal, performance (EAP) profiles. These links between emotions, appraisals, and performance can extend over seconds, but also over days, weeks or years (Turner & Waugh, 2007), meaning that EAP profiles may emerge on both the momentary state level as well as the more stable trait level. For example, whereas some learners show low math performance (i.e., low grades), experience negative emotions around math, consider themselves being bad in math, and value math negatively, other learners may show the opposite profile of high performance, positive emotions, high confidence and value. The aim of this study is to reveal whether qualitatively different profiles can be identified in the domain of math, considering emotions, appraisals and performance. This is done using model-based latent profile analysis, both at a more stable trait-level and an activity-related state-level, on which two contexts are considered.

1. Relations between achievement emotions, appraisal and performance

Broadly speaking, CV-theory (Pekrun, 2006; Pekrun et al., 2017) posits that learners' appraisals of control and value, in interaction with the object focus of the achievement situation, are important determinants of their emotions. An appraisal of control over an achievement task depends on the learners' perceived capabilities to influence and succeed in the achievement situation. An appraisal of the value of the outcome of an achievement task can be related to learners' intrinsic or extrinsic (i.e., test grade, perceived importance for future) appreciation of the activity. The object focus of the learner concerns whether the achievement situation is a future event (outcome/prospective), a past event (outcome/retrospective) or related to a (current) activity. According to CV-theory, the levels of appraisals of control and value in combination with the object focus is crucial for the achievement emotions experienced and their intensity. For example, lacking the

* Corresponding author.
E-mail addresses: M.S.M.Sachisthal@uva.nl (M.S.M. Sachisthal), M.E.J.Raijmakers@uva.nl (M.E.J. Raijmakers), B.R.J.Jansen@uva.nl (B.R.J. Jansen).

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confidence that one will succeed on an important (high value) upcoming math test (low control of a prospective event), may result in feelings of anxiety or even hopelessness. Working on a math task (current activity) that is perceived as useful (high value) and feeling confident that one can do well may result in enjoyment.

The emotions that may arise can be classified by their valence and activation (Barrett & Russell, 1998; Pekrun et al., 2011). Positive activating emotions, such as enjoyment, have been shown to be positively bidirectionally linked with performance (Pekrun et al., 2017; Pinxten et al., 2014; Putwain et al., 2018), whereas negative deactivating emotions, such as boredom have been shown to be negatively bidirectionally linked with performance (Pekrun et al., 2017; Pinxten et al., 2014; Putwain et al., 2018). While bidirectional relations between negative activating emotions, such as anxiety and anger, and performance have been shown to be negative (Pekrun et al., 2017), some studies on the state level have found that low to moderate levels of anxiety may lead to higher persistence in difficult tasks (Tulis & Fulmer, 2013). High levels of math anxiety are consistently negatively correlated with math performance, though (see Namkung et al. (2019) for a Meta-Analysis), which is likely due to a higher working memory load of individuals with high levels of anxiety (Ashcraft & Kirk, 2001; Suárez-Pellicioni et al., 2016).

1.2. Profiles in achievement emotions

The above shows that cause and effect cannot be clearly

Table 1
Overview of studies investigating affective profiles in an academic context, in chronological order.

Author(s)	Context	N	Emotions	Outcome variables/ predictors	Profiles (as named in publication)	Results
Tulis and Ainley (2011)	Study 1: Adaptive training software in mathematics class Gymnasium[a]; over 5 weeks; Mean age = 10.5	182	*State emotions* Enjoyment, pride, interest, relief, boredom, anger, sadness, shame and anxiety (choose up to 3 and rate their intensity)	*Predictors* Mathematics achievement Self-concept of ability Subject value Error orientation	*After success:* 1) Bored and angry (8%) 2) Positive (32%) 3) Unemotional (61%) *After failure:* 1) Angry and bored (33%) 2) Positive (16%) 3) Unemotional (46%) 4) Anxious and despondent (5%)	Profiles only related to error orientation: *After success:* Profile "bored and angry" lower error orientation than other profiles; *After failure:* Profile "bored and angry" lower than other profiles
	Study 2: Adaptive training software in mathematics class Gymnasium; over 5 weeks; Mean age = 10.8	135	*State emotions* Enjoyment, pride, interest, boredom, anger, shame and anxiety (choose up to 3 and rate their intensity)	*Predictors* Mathematics achievement Goal orientation Causal beliefs	*After failure:* 1) Angry and bored (19%) 2) Positive (25%) 3) Unemotional (50%) 4) Ashamed and despondent (6%); Profiles 1 and 4 combined: Negative affect profile	Profiles related to goal orientation: Positive profile higher mastery goal orientation than negative affect profile; Profiles related to causal beliefs: Positive profile higher effort causal beliefs than negative affect profile
Jarrell et al. (2015)	Intelligent tutoring system for first- and second-year medical students; Mean age = 23	30	*Outcome/retrospective* Pride, joy, relief, anger and shame	Performance	1) Low affect 2) Negative affect 3) Positive affect	Profiles related to performance: Positive affect profile had highest performance; Negative affect profile had: lowest performance
Jarrell et al. (2016)	Intelligent tutoring system for pre- and medical students; Mean age = 24.40	26	*State emotions (test)* enjoyment, pride, hope, anxiety, hopelessness, shame and anger	Control Value Perceived performance Performance	1) Positive emotion (N = 7) 2) Negative emotion (N = 5) 3) Low emotion (N = 13)	Control: Positive emotion profile higher than negative emotion profile Value: Positive emotion profile higher than negative emotion profile
Ganotice et al. (2016)	Study 1: Secondary school students from Philippines Mean age = 14.19	1147	*Domain-general trait* Enjoyment, hope, pride, anger, anxiety, shame, hopelessness, boredom	Motivation	1) Adaptive shame (36.5%) 2) Moderate (25.3%) 3) Maladaptive (19.9%) 4) Adaptive (18.3%)	Autonomous and controlled motivation: Highest in adaptive shame profile and adaptive profile
	Study 2: Secondary school students from Philippines Mean age = 13.53	341	*Mathematics trait* Enjoyment, hope, pride, anger, anxiety, shame, hopelessness, boredom	School engagement Achievement	1) Adaptive shame (34.9%) 2) Maladaptive (26.4%) 3) Moderate (26.7%) 4) Adaptive (12%)	School engagement: Adaptive shame profile and adaptive profile higher scores Achievement: Maladaptive profile and moderate profile lower achievement
Robinson et al. (2017)	Undergraduate anatomy and physiology course Mean age not reported	278	*Activity (last three lectures)* joyful, excited, enthusiastic, energetic, happy, ease, relaxed, calm, annoyed, irritated, agitated, angry, exhausted, worn out, tired	Behavioral engagement and disengagement Achievement	1) Positive (40%) 2) Deactivated (21%) 3) Negative (15%) 4) Moderate-low (25%)	Mediation: Higher achievement for positive and deactivated profiles due to less behavioral disengagement

The difference between state vs. outcome/retrospective emotion is that state emotion is measured during or after a task with no feedback given, whereas outcome/retrospective emotion is measured after receiving feedback.

[a] Gymnasium is the highest academic track in the German school system.

distinguished in the learning process. Although performance is often seen as the outcome, it can also be considered as a cause of emotions and appraisal. A profile shows a learner's levels in emotions, appraisal and performance, without assigning cause and effect. Given our interest in such *qualitatively* different subgroups of individuals based on their profiles of emotions, appraisals and performance in a math context, we used a person-centered approach and not the commonly used variable-centered analytical approach. When using variable-centered analytical approaches (e.g., general linear models) possible differences in math performance can be attributed to a predictor such as math anxiety (e.g., Devine et al., 2012). Person-centered approaches, such as profile analysis, on the other hand, focus on the individual rather than the variable - meaning that the focus shifts to the manifestation of a variable in relation to other variables. In profile analysis, *qualitatively* different subgroups of individuals are unveiled (Bergman et al., 2003; Collins & Lanza, 2010; Hickendorff et al., 2018; Sterba & Bauer, 2010).

Different studies have investigated profiles of achievement emotions and their relation with different predictors or (mal-)adaptive academic outcomes (see Table 1 for an overview; Ganotice et al., 2016; Jarrell et al., 2016, 2015; Robinson et al., 2017; Tulis & Ainley, 2011). Even though the studies differed in the conceptualization and measurement of the achievement emotions (e.g., state vs. trait emotions; domain general vs. domain specific; retrospective measures vs. state measures) as well as the population studied (ranging from secondary school students to college students), in all studies, three comparable achievement emotions profiles emerged: A positive (adaptive) profile, marked by higher levels of positive emotions (e.g., pride, enjoyment) and lower levels of negative emotions; a negative (maladaptive) profile, marked by higher levels of negative emotions (e.g., boredom, anger) and lower levels of positive emotions; and an unemotional (or low affect / moderate) profile, marked by lower levels on all emotions. In some samples a fourth profile emerged, characterized by an additional negative emotion – such as shame and anxiety (Ganotice et al., 2016; Tulis & Ainley, 2011), or feelings of being calm, but worn out (Robinson et al., 2017). The found emotion profiles match with results on the co-occurrence of emotions of similar valence, which co-occur on both the trait (e.g., Nett et al., 2017; Peixoto et al., 2017; Pekrun et al., 2011; Watson & Clark, 1992) and the state level (e.g., Nett et al., 2017; Vansteelandt et al., 2005; Zelenski & Larsen, 2000). Emotions of differing valence seem to be independent on the trait level (Nett et al., 2017; but see Pekrun et al., 2011), meaning that learners may associate math with both enjoyment and anxiety, but seem to be negatively correlated on the state level - within the same learning situation, a learner will not enjoy the task and feel bored at the same time.

Remarkably, these studies applied profile analysis on emotions only, whereas relations with appraisals or performance were expected by the authors, which were only studied as possible predictors and/or outcomes of emotion profiles. Instead of (somewhat arbitrarily) regarding appraisals and/or performance as predictors and/or outcomes of membership of a specific emotion profile, we include measures of appraisal and performance, together with measures of achievement emotions, so that each contributes to the identification of profiles. Including not only emotions, but also appraisals and performance in the latent profile analysis, will thereby draw a more complete picture of the interrelations of the variables.

1.3. Trait and state

As mentioned earlier, academic emotions can be assessed at different levels, namely on a more habitual trait level and on an activity-related state level (Pekrun, 2006) at which emotions fluctuate and change rapidly. Generally, learners rate trait emotions higher than state emotions (Bieg et al., 2014); which is thought to be due to accessibility (Robinson & Clore, 2002): As trait emotions are not directly accessible, people will resort to episodic experiences and beliefs like self-concept and stereotypes when asked to report them.

Around half of the variance of state emotions experienced in relation to learners' math class is attributable to the situation and half to trait-like antecedents (Nett et al., 2017). The importance of the situation implies that when studying state emotions, the context (i.e., studying for a test, working on a math task) can affect which state emotion is experienced. In this study, we investigate whether EAP profiles are situation-specific by presenting participants with two types of math tasks, one with a high level of control, and the other with a low level of control. Moreover, the importance of trait-like antecedents for emotions experienced in math class implies that trait and state emotion profiles are likely related.

1.4. Overview of the current study

The aim of the present study was to map profiles of achievement emotions, appraisals and performance on both a trait and state level in the domain of math by using a person-centered analysis. Regarding emotions, the choice was made to measure anxiety, enjoyment, anger, and boredom. Anxiety is the emotion most often associated with mathematics (Carey et al., 2016; Ramirez et al., 2018; Suárez-Pellicioni et al., 2016); enjoyment is a positive, activating achievement emotion that has been shown to be predictive of math performance (e.g., Hagenauer & Hascher, 2014), and anger and boredom may be especially important in current academic activities (Pekrun, 2006). Achievement emotions, appraisals, and performance are analyzed simultaneously, using a model-based latent profile analysis approach. The study adds to the existing literature by (1) employing a person-centered approach, thereby allowing for the identification of possible subgroups of learners with qualitatively distinct patterns of relations between variables; (2) including not only achievement emotions but also appraisals and academic performance, ensuring that these variables will all contribute to the identification of the profiles and not making any (arbitrary) choices on which variables are predictors and/or outcomes; (3) investigating the relation between trait and state profiles. More specifically, we investigate trait and state mathematics EAP profiles, with a variation in the situational context, by having two conditions of a math task (choice vs. no choice). Three different profile analyses are thus computed: one on the trait level and one per math task condition.

First, we hypothesize that meaningful profiles will emerge on both the trait and the state level (Hypothesis 1). Second, on the trait level, we expect that three EAP profiles emerge (Hypothesis 2). Due to the finding of strong relations between emotions of similar valence (e.g., Nett et al., 2017; Pekrun et al., 2011) and based on previous profile analysis results (e.g., Jarrell et al., 2015; Tulis & Ainley, 2011), we expect a positive and a negative trait EAP, with positive (negative) emotions being high in the positive (negative) trait EAP. Due to bidirectional couplings of appraisals and performance with emotions, we expect high (low) levels of control and value and performance in the positive (negative) trait EAP (Hypotheses 2.1, 2.2). A third, neutral trait EAP is expected to emerge, with levels on all constructs being in between the other two trait EAPs (Hypothesis 2.3). Third, on the state level, the emerging profiles are expected to be dependent on the situational context (Nett et al., 2017; Tulis & Ainley, 2011), resulting in different EAP profiles for the choice and the no choice task (Hypothesis 3). Though value may be rather low in both conditions due to the task not being relevant for students' grades, the conditions are expected to differ in perceived control. Hence, we expect that generally, more extreme (negative) EAPs may emerge in the no choice condition, given lower levels of control (Hypothesis 3.1). The dominant emotion is expected to depend on the difficulty of the math problems (Hypothesis 3.2). If the math problems are experienced as difficult, state EAPs marked by higher levels of anxiety (perceived low control) and enjoyment (perceived high control) may emerge, whereas state EAPs marked by boredom and anger are expected if the math problems are easy. Fourth, we expect trait and state EAPs to be related, given the importance of trait-variance in emotional state experiences (Nett et al., 2017) (Hypothesis 4). Lastly, we expect to find gender differences in the number of individuals within the profiles (Hypothesis 5):

Generally, girls may be overrepresented in any EAPs marked by relatively high levels of anxiety and lower levels of control appraisals, especially on the trait level (Bieg et al., 2015; Else-Quest et al., 2010; Frenzel et al., 2007; Goetz et al., 2013; Kenney-Benson et al., 2006; but see Orbach et al. (2019), who found gender effects on both the trait and state level) (Hypothesis 5.1), whereas boys may be overrepresented in any EAPs marked by higher levels of boredom (Pekrun et al., 2010, 2017) (Hypothesis 5.2).

2. Method

2.1. Participants

Students were recruited through their schools; 17 classes from five different schools from a metropolitan area in the Netherlands agreed to participate. Parents received an information letter about the study and could refuse permission for participation of their child. The study was approved by the local Ethics Committee (reference code: 2018-COP-8746). Participants were 384 Dutch teenagers of middle schools (50% girls, 1 sex unknown; 169 first grade, 214 s grade, 1 unknown; $M_{age} = 12.88$, $SD_{age} = 0.70$). All students followed selective secondary education tracks HAVO (*"higher general continued education"*) or VWO ("*preparatory scientific education*"). The first class that participated ($N = 25$) was excluded due to technical issues. Additionally, 11 students' data were excluded due to technical issues, such as the same identifier being recorded for multiple participants. Data of the remaining 348 participants (52% girls; 141 first grade, 207 s grade; $M_{age} = 12.92$, $SD_{age} = 0.71$) were included in the analyses.

2.2. Procedure

Data collection took place in March 2018. All questionnaires and tasks were computer-administered within the classroom, all independent of lesson materials. In total the study took around 45 min. Order of administration of instruments was 1) questionnaires assessing trait emotions and appraisals (in random order); 2) math task, during which state measures were recorded; 3) questionnaire on background variables, instrumental value of mathematics, and current mathematics grade.

2.3. Materials

2.3.1. Trait measures[1]

All trait measures were administered in Dutch and mean scores were transformed to z-scores for the analyses. We report McDonald's omega as a measure for internal consistency, as it does not assume tau-equivalence of indicators (Hayes & Coutts, 2020).

2.3.1.1. Anxiety. Trait anxiety was measured using the Abbreviated Math Anxiety Scale (AMAS; Hopko et al., 2003). Across nine items, participants were asked to indicate, on a 5-point Likert scale from (1) "(almost) not anxious" to (5) "very anxious", how anxious they would feel in a given situation (i.e., before a test, during homework, during class). An example item is "Taking an examination in a math course". Internal consistency in our sample was high, McDonald's $\omega = 0.89$.

2.3.1.2. Enjoyment, anger, and boredom. Trait emotions enjoyment, anger and boredom were measured using the corresponding subscales from the Academic Emotions Questionnaire-Mathematics (AEQ-M; Pekrun et al., 2005). Participants were asked to indicate, on a 5-point Likert scale from (1) "strongly disagree" to (5) "strongly agree", how they *typically* feel in situations related to learning, doing homework or taking a test in mathematics class. The subscales consisted of three enjoyment[2] (e.g., "I enjoy taking tests in mathematics."), four anger (e.g., "My mathematics homework makes me angry."), and five boredom (e.g., "I can't concentrate because I am so bored.") items. The internal consistency of the three subscales used was acceptable to high in our sample; McDonald's $\omega = 0.73$, 0.84 and 0.85, respectively.

2.3.1.3. Perceived trait control. Perceived control in mathematics was measured using the self-concept questionnaire of the PISA 2012 measure (OECD, 2013). Participants were asked to indicate their agreement with five statements concerning their learning of math (e.g., "I am just not good at mathematics (reversed)") on a 4-point Likert scale from (1) "strongly disagree" to (4) "strongly agree". In our sample, the internal consistency of the scale was high, McDonald's $\omega = 0.90$.

2.3.1.4. Perceived trait value. Perceived value of mathematics was measured using the instrumental motivation for studying mathematics questionnaire of the PISA 2012 measure (OECD, 2013) On the four items, participants indicated how much they agreed with different statements on mathematics (e.g., "Learning mathematics is worthwhile for me because it will improve my career prospects") on a 4-point Likert scale from (1) "strongly disagree" to (4) "strongly agree". In our sample, the internal consistency of the scale was high, McDonald's $\omega = 0.89$.

2.3.1.5. Performance in general. To assess mathematics performance, participants were asked to indicate their current math grade. In the Dutch system, grades range from 0 to 10, with grades above 5.5 being a pass.

2.3.2. State measures

All state measures were measured within a math task, as represented in Fig. 1.

2.3.2.1. Math task. The version of the Amsterdam Math Anxiety Task (AMAT; (Schmitz, 2020) used in the current study consisted of two conditions, with each participant being presented with both conditions in randomized order. In each condition, 12 4-choice mathematics problems of three difficulty levels[3] (level 1 - level 3) were presented. No feedback was given. In the *choice* condition, participants were able to choose between two difficulty levels per trial, meaning that the amount of trials per difficulty level may have differed between participants; additionally, they were able to change their answer. In the *no choice* condition, participants did not have a choice - they were presented with four items per difficulty level, which were presented in randomized order; they were not able to change their answer. Participants reported state emotions and appraisals of control and value before the task started (after three example math items), and after each condition. State enjoyment and anxiety were additionally measured once within each condition. Only the measures after each condition were used in the current study, as all emotions and the two appraisals were assessed at that time point.

2.3.2.2. State emotions. To assess state emotions, learners answered two

[1] We also measured self-efficacy as an indexof trait control and intrinsic value as an index of trait value. The two questionnaires were removed at the request of a reviewer, which was based on confirmatory factor analyses. For more information, see the supplementary materials.

[2] Initially, four items were used to assess enjoyment. As one item reduced internal consistency to McDonald's $\omega = 0.69$, we excluded that item ("I am happy that I understand the material.").

[3] Equations in level 1 had the form $x + (-) b = y$, with x and y values between 11 and 99. Equations in level 2 and 3 had the form $ax + (-) b = y$, with x ranging from 1 to 9 and b and y having values between 11 and 99. In level 2, a ranged from 2 to 5, while ranging from 6 to 9 in level 3. Carry procedures were required for all equations on level 1 and 3, but not for level 2. No decimal values, negative values or multiples of ten were used.

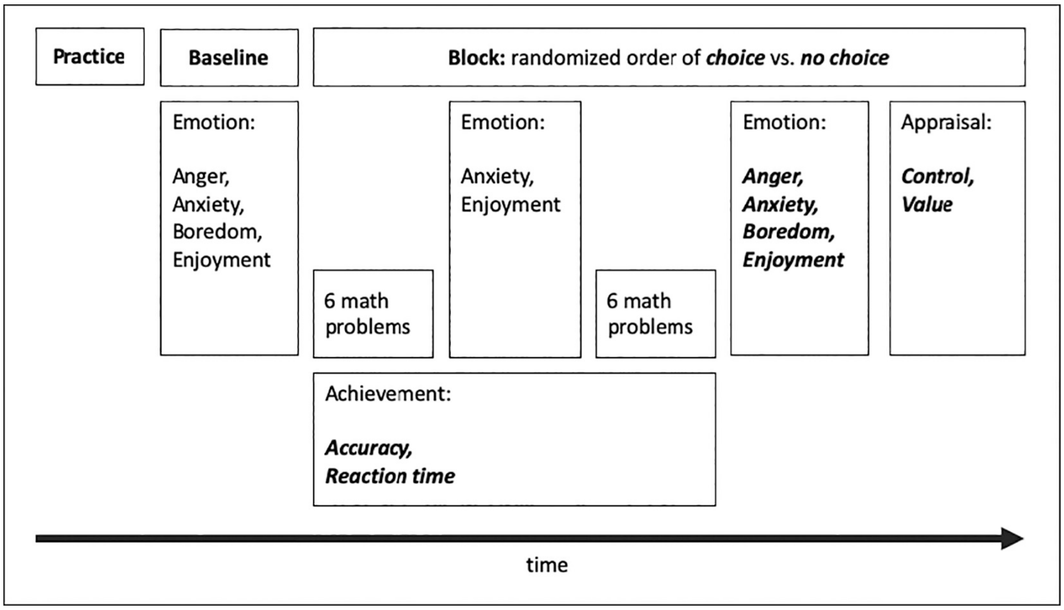

Fig. 1. Overview of the state measures taken during the math task (Schmitz, 2020).
Note. Only the measures in bold and cursive are included in the present study.

questions per emotion (e.g., "How [happy/anxious/angry/bored] are you at this moment?") on a Visual Analogues Scale (VAS; see Abend et al., 2014; van Duinen et al., 2008), ranging from 0 ("not at all") to 1 ("very much so"). The relative location on the scale that was clicked determined the state emotion score.

2.3.2.3. Perceived task control and value. To assess task appraisals, participants answered one question on perceived task control ("How much control did you feel you had during the last block?") and two on perceived value of the task (e.g., "How useful did you find the task so far?")[4] on a VAS scale ranging from 0 ("not at all") to 1 ("very much so"). The relative location on the scale that was clicked determined the perceived control and value score.

2.3.2.4. Performance. Per condition, performance was measured using the percentage of correctly answered items per difficulty level. We also measured reaction times (RTs). RTs can indicate levels of (mental) effort and/or ability (Humphreys & Revelle, 1984), but interpretation requires taking into account accuracy and item difficulty. Speed on correctly solved *difficult* items (high working memory lead) is positively related to ability but speed on correctly solved *easy* items can also be positively related to effort. For incorrect responses, interpretation is more complicated. For difficult items, fast incorrect responses may indicate low effort, whereas slow incorrect responses may indicate low ability or distraction (Trezise & Reeve, 2014). For easy items, fast incorrect responses may indicate low effort, whereas slow incorrect responses may indicate distraction. To reduce complexity of interpretation, only reaction times of correctly solved items will be considered.

3. Results

All analyses were run in *R* (R Core Team, 2019), see the supplementary materials for the complete R code.

3.1. Analytic strategy/data cleaning

Raw data were first examined for possible outliers and violations of normality, as these may impact the results of latent profile analyses (Hair Jr. et al., 2009). Outliers were detected using the median absolute deviation (MAD) procedure (Leys et al., 2013) with a cut-off value of 3 (very conservative). All variables were standardized before running the profile analysis to ease interpretation and plotting.

3.1.1. Trait measures

Although 43 participants (13%) had scores that were detected as outliers, all measures had acceptable values of skewness and kurtosis, all $<|1.96|$ (Henderson, 2006), even when including outliers. We therefore did not remove the outliers, but see the supplementary materials for the results with outliers removed. Only the data of one participant were removed, as the participant showed aberrant behavior (i.e., choosing the answer option 1 across all questions). Table 2 shows the descriptive statistics; Table S5 (supplementary material) contains the correlations of all included measures.

3.1.2. State measures

Detected outliers on the emotion and appraisal measures represented individuals scoring particularly high (on anxiety, boredom). In the no choice [choice] condition, 52 [58] participants (16%) [17%] had scores that were detected as outliers. In the no choice condition, emotion and appraisal measures had acceptable values of skewness and kurtosis, all $<|1.96|$, even when including outliers; outliers were therefore not removed. In the choice condition, emotion and appraisal measures had acceptable values of skewness and kurtosis $<|1.96|$, besides the state anxiety measure (kurtosis = 3.79). Because only one measure had high kurtosis and for comparability across conditions, outliers were not removed, but see the supplementary materials for the results with outliers removed.

All accuracy scores, by difficulty level and overall, showed a serious ceiling effect; accuracy scores were therefore not included in our analyses. Instead, we interpreted RTs for *correctly solved* math items as indicators of ability and/or effort - similarly to inverse efficiency scores (IES; Bruyer & Brysbaert, 2011; Townsend & Ashby, 1978), in which RT is divided by accuracy, higher scores indicate worse performance (i.e., due to lower ability, less effort). Given the ceiling effect, we can assume

[4] While the wording of the two state appraisals differed (control question referred to the last block vs. value referred to the task so far), no differences across conditions were found on either measure ($p > .1$).

Table 2
Descriptive statistics of the measures included in the trait and state profiles.

Trait level

	N	Emotions[1] Anger *M (SD)*	Anxiety *M (SD)*	Boredom *M (SD)*	Enjoyment *M (SD)*	Appraisals[1] Control *M (SD)*	Value *M (SD)*	Performance[2] Grade *M (SD)*
Total	338	2.06 (0.95)	1.93 (0.73)	2.42 (0.93)	2.20 (0.88)	2.59 (0.74)	2.88 (0.73)	6.91 (1.23)
Moderate	250	1.65 (0.51)***	1.75 (0.52)***	2.16 (0.73)***	**2.32 (0.81)****	**2.73 (0.64)*****	**3.03 (0.62)*****	**7.19 (1.12)*****
Maladaptive	88	**3.21 (0.97)*****	**2.45 (0.98)*****	**3.10 (1.04)*****	1.87 (0.98)**	2.18 (0.84)***	2.47 (0.84)**	6.12 (1.21)***

State level - no choice condition

	N	Anger[3] *M (SD)*	Anxiety[3] *M (SD)*	Boredom[3] *M (SD)*	Enjoyment[3] *M (SD)*	Control[3] *M (SD)*	Value[3] *M (SD)*	Reaction time correct *M (SD)*
Total	332	0.26 (0.25)	0.17 (0.18)	0.57 (0.18)	0.39 (0.23)	0.66 (0.24)	0.40 (0.23)	18413 (8526)
Adaptive	103	.06^{a} (0.03)	.07^{a} (0.05)	.42^{a} (0.25)	**.55^{a} (0.19)**	**.73^{a} (0.22)**	**.50^{a} (0.21)**	14807^{a} (5655)
Moderate	123	.21^{b} (0.11)	.22^{b} (0.15)	.53^{b} (0.20)	.46^{b} (0.16)	.67^{a} (0.18)	.47^{a} (0.16)	19094^{b} (8850)
negEmo-lowerApp	48	**.64^{c} (0.23)**	**.39^{c} (0.26)**	.65^{c} (0.29)	.20^{c} (0.17)	.57^{b} (0.29)	.30^{b} (0.21)	**22750^{c} (8630)**
bored-lowValue-slow	58	.39^{d} (0.25)	.07^{a} (0.05)	**.86^{d} (0.10)**	.14^{c} (0.09)	0.64 (0.30)	.15^{c} (0.12)	19781^{b,c} (9677)

State level - choice condition

	N	Anger[3] *M (SD)*	Anxiety[3] *M (SD)*	Boredom[3] *M (SD)*	Enjoyment[3] *M (SD)*	Control[3] *M (SD)*	Value[3] *M (SD)*	Reaction time correct *M (SD)*
Total	328	0.22 (0.22)	0.15 (0.16)	0.57 (0.28)	0.41 (0.23)	0.69 (0.24)	0.40 (0.22)	13,917 (6458)
Adaptive	154	.08^{a} (0.05)	.08^{a} (0.05)	.42^{a} (0.22)	**.53^{a} (0.19)**	**.73^{a} (0.20)**	**.51^{a} (0.19)**	12241^{a} (5136)
Moderate	74	.27^{b} (0.12)	.32^{b} (0.15)	.49^{b} (0.19)	.42^{b} (0.17)	.66^{a} (0.18)	.46^{a} (0.15)	**16062^{b} (6196)**
negEmo-lowerApp	23	**.68^{c} (0.17)**	**.42^{c} (0.27)**	.78^{c} (0.29)	.20^{c} (0.23)	.52^{b} (0.33)	.18^{b} (0.17)	14,055 (6637)
bored-lowValue-slow	77	.32^{b} (0.25)	.06^{a} (0.04)	**.88^{c} (0.10)**	.22^{c} (0.20)	.67^{a} (0.29)	.18^{b} (0.15)	15165^{b} (8060)

Trait level: Significance levels: *** <0.001, ** < 0.01, * <0.05.
State level: For each dependent variable, bolded means are the highest mean scores, means with different subscripts indicate a significant difference at $p < .05$ using Tukey multiple comparisons of means. Means in the same column are significantly different between profiles if they have different subscripts.
Note: Abbreviations: negEmo-lowerApp = Negative emotion, lower control & value profile; bored-lowValue-slow = Bored, low value, slow profile.
[1] Range 1–5.
[2] Range 1–10.
[3] Range 0–1.

that the math task was easy, so that we interpret lower (higher) RT scores as indicative of higher (lower) effort and/or ability. Outliers on the RTs represented particularly slow trials and were removed. To limit possible condition effects on RTs, namely that participants were able to choose a difficulty level and change their answer before submitting in the choice condition, only RTs of the initial correct choices for items of level 2[5] were included. See Table 2 for descriptive statistics and Table S5 (supplementary material) for the correlations between all included measures.

3.2. Latent profile analysis

A model-based latent profile analysis (LPA) was used to identify profiles on both the trait and the state level, employing the Mclust function of the *Rpackage* mclust (Scrucca et al., 2016). Through maximizing a log-likelihood function, Mclust simultaneously estimates parameters (i.e., profile sizes, means and covariances of the variables in each profile) of models differing in number of profiles (1–9), volume (profile size), orientation (in multidimensional space) and shape (spherical, diagonal or ellipsoidal). Mclust selects the best model based on the lowest Bayesian Information Criterion (BIC). BIC penalizes complexity while rewarding parsimony (Fraley & Raftery, 1998; Mun et al., 2008; Raftery & Dean, 2006). Profile membership is then determined per participant based on the highest posterior probability. Model-based latent profile methods are quite robust to multivariate non-normality (Hardin & Rocke, 2004; Yeung et al., 2001).

Chi-square tests were used to check whether (1) sex was related to profile membership and (2) profile membership across state and trait and the two state conditions were related. Cramér's V (ϕ) is reported as a measure of effect size for the Chi-square tests (Cohen, 1988; Ellis, 2010). Differences between profiles in profiling variables were tested by running a between subject Anova-test per profiling variable with profile membership as predictor. Post hoc *t*-tests were run when the Anova-test was significant, controlling for multiple comparisons using Tukey test for multiple comparisons.

As suggested by Wormington and Linnenbrink-Garcia (2017), labeling of profiles was driven by the most salient characteristic of the profile based on raw values, which was labeled high or low (vs. moderate) if it was closer to the end- than the midpoint of the scale. The other variables were considered afterwards.

3.2.1. Trait profiles

The trait latent profile analysis was based on a sample of $N = 338$, due to missing grades. An ellipsoidal, equal shape and orientation model with two profiles was selected (log likelihood = −2860.81; BIC = −5977.84)[6,7]. The profile solution is displayed in Fig. 2 and Table 2 (upper part). The two profiles differed significantly on all included measures.

The first and larger profile ($N = 250$; 74%) consisted of students reporting low levels of anger and anxiety and moderate levels of all

[5] Levels 1 and 3 were not sufficiently often chosen in the choice condition; therefore, only RTs correct for level 2 were included in the analyses.

[6] See Table S6 in the supplementary materials for a description and the fit BIC of the top three best fitting models.

[7] When outliers were removed, two profiles emerged on the trait level. The two profiles were similar in size, with one profile being maladaptive and one moderate. The results of the profile analysis with and without outliers were not independent ($p < .001$).

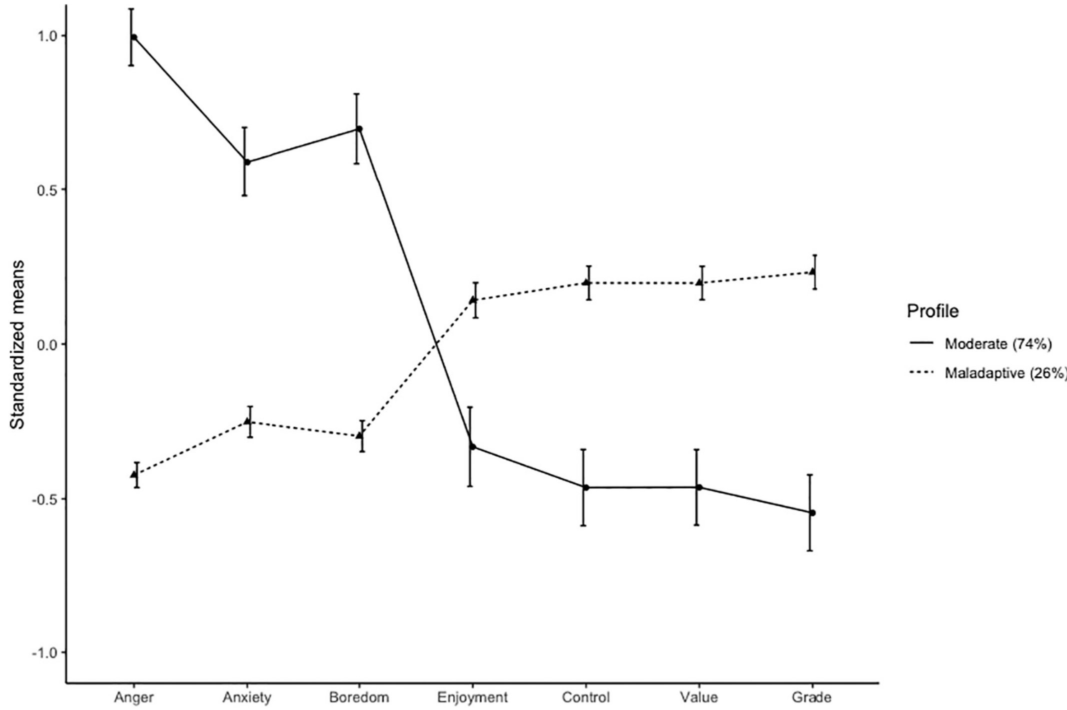

Fig. 2. Profile plot of the two trait EAPs.
Note. The *y axis* represents the standardized mean score per measure. Please note that the lines in the plots do not represent relationships between variables, but are used as a visualization of the two profiles.

remaining variables. In comparison with the second profile, scores on the positive variables (enjoyment, control and value appraisals, performance) were significantly higher and scores on the negative emotions (anger, anxiety, boredom) were significantly lower. This profile will be referred to as *moderate* as most scores were in a moderate range.

The second and smaller profile ($N = 88$; 26%) consisted of students reporting low levels of intrinsic value and moderate levels on all reported emotions and other appraisals as well as performance. We therefore labeled this profile *maladaptive profile.*

Chi-square analyses revealed that trait profile membership was dependent on students' sex, χ^2 (1, $N = 338$) = 4.54, $p = .03$, $\phi = 0.12$. Girls were more likely to be in the *moderate* profile than predicted and boys were more likely to be in the *maladaptive* profile than predicted.

3.2.2. State profiles

The profile solution for both the no choice ($N = 332$) and the choice ($N = 328$) condition yielded a model with an ellipsoidal, equal orientation with four profiles being the best fitting model (*no choice*: log likelihood = −2627.61; BIC = −5719.64 [*choice*: log likelihood = −2579.24; BIC = −5621.92][8])[9]. The profile solution is displayed in Fig. 3 and in the middle and lower part of Table 2.

First, an *adaptive* profile emerged, being the second largest profile in the no choice ($N = 103$; 31%) and the largest profile in the choice condition ($N = 154$; 47%). In this profile, levels of anger and anxiety were low, levels of boredom, enjoyment and value medium, levels of control were medium to high and RTs low (indicating higher effort and/or ability). Levels of anger and boredom (enjoyment) were the lowest (highest) as compared to the other profiles. Reported anxiety levels were lower than those in the second and third profile. Appraisals of control and value were relatively higher and effort and/or ability relatively higher than in the other profiles.

Second, a *moderate* profile emerged, being the biggest profile in the no choice condition ($N = 123$; 37%) and the third biggest profile in the choice condition ($N = 74$; 23%). In this profile, levels of anger and anxiety were low to moderate, levels of boredom, enjoyment and value were moderate, levels of control were moderate to high and RTs high. While reporting similar levels of control and value appraisals as members of the *adaptive* profile, levels of anger, anxiety and boredom (enjoyment) were significantly higher (lower) and RTs were higher (indicating lower effort and/or ability). In comparison with profiles three and four, generally, the *moderate* profile had higher (lower) levels of enjoyment, control and value appraisals (anger, boredom), with levels of anxiety being higher (lower) than the fourth (third) profile. RTs were lower than those of the third profile, but only in the no choice condition.

Third, a *negative emotion-lower appraisals* (*negEmo-lowerApp*) profile emerged, being the smallest in both the no choice ($N = 48$; 15%) and the choice condition ($N = 23$; 7%). In this profile, levels of the three negative emotions as well as control were moderate to high, levels of enjoyment and value were low to moderate and RTs high (moderate) in the no choice (choice) condition. Levels of negative emotions (enjoyment, appraisals of control and value) were higher (lower) than those in the first two profiles. Only in the no choice condition RTs were higher (indicating low effort due to the high boredom levels) than those of the first two profiles. Levels of anger and anxiety were higher than in the fourth profile. In the no choice condition, levels of boredom (value) were higher (lower) than in the fourth profile. In the choice condition, levels of control were lower than in the fourth profile.

Fourth, a *bored and low value, slow* (*bored-lowValue-slow*) profile emerged, being the second smallest profile in the no choice condition ($N = 58$, 17%) and the second biggest profile in the choice condition ($N = 77$; 23%). In this profile, levels of anxiety, enjoyment and value were low, levels of anger were moderate, levels of boredom high and RTs high. Setting this profile apart from the *negative emotion, lower appraisals* profile are significantly lower levels of anger and anxiety. Moreover,

[8] Brackets are used to denote results for the choice condition.

[9] When outliers were removed, three similar profiles emerged for both state conditions: an adaptive profile, an anxious profile and a negative profile. The results of the profile analysis with and without outliers were not independent (both $p < .001$).

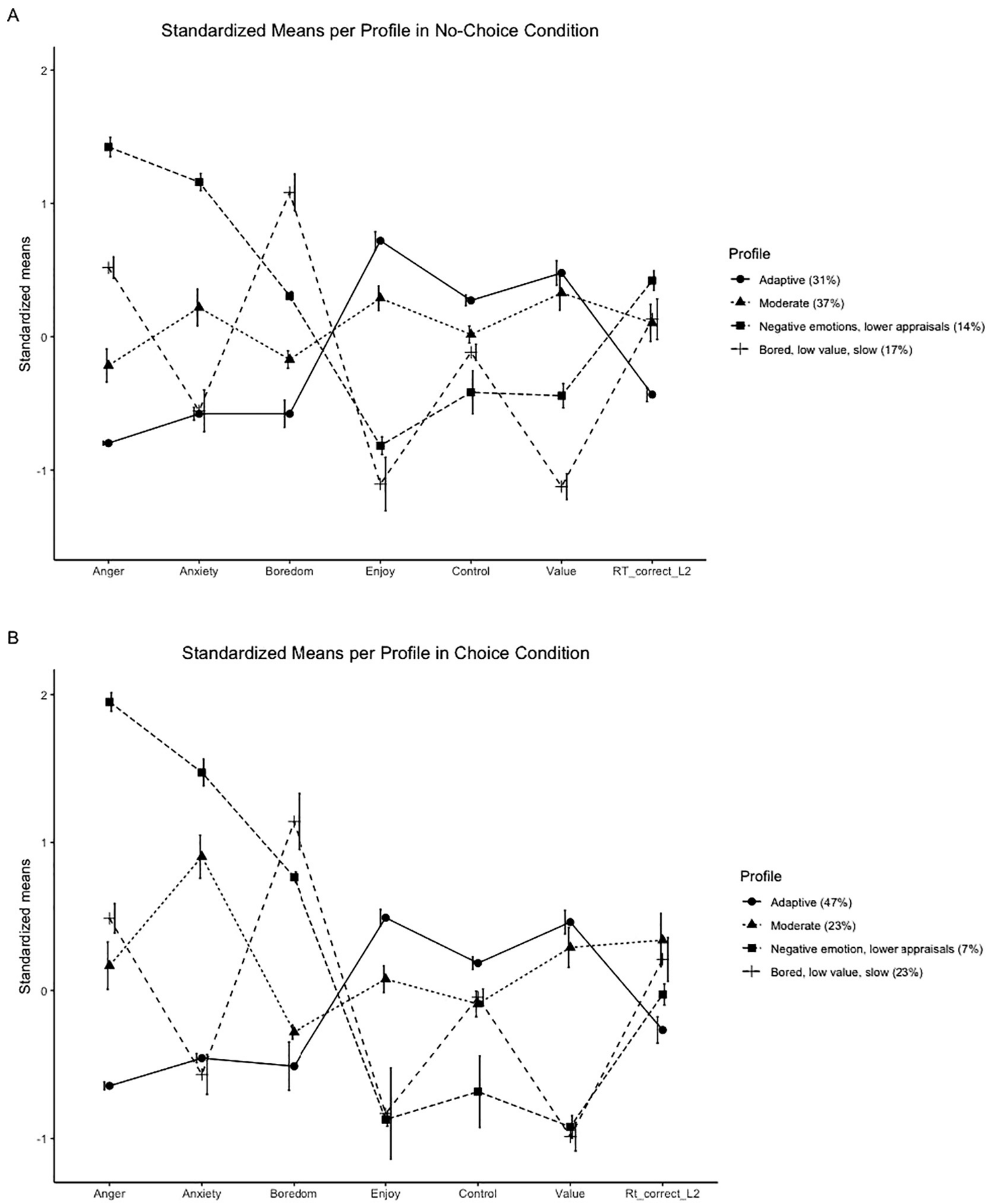

Fig. 3. Profile plots of the four state EAPs for the no choice condition (panel A) and the choice condition (panel B).
Note. The *y axis* represents the standardized mean score per measure. Please note that the lines in the plots do not represent relationships between variables, but are used as a visualization of the four profiles.

individuals in this profile had higher RTs than those in the first profile (indicating less effort and/or ability).

Summarising, similar profiles emerged across conditions, but they differed in their size, with more than half of the participants belonging to the *adaptive* profile in the choice and only one third of participants belonging to the same profile in the no choice condition. Moreover, the relation between profiles slightly differed between choice conditions, most notably the *negEmo-lowerApp* profile, which differed from the *bored-lowValue-slow* profile on different measures depending on the condition (choice / no choice).

State profiles per condition were not independent, χ^2 (9, 316) = 190.93, $p < .001$, $\phi = 0.45$. This dependency was driven by overlapping profile memberships (i.e., students belonging to the adaptive profile in both conditions). Also, of students in the *moderate* profile of the choice condition, more individuals than predicted belonged to the *negEmo-lowerApp* profile in the no choice condition. In Fig. 4, the distribution of individuals across state profiles is displayed in a mosaic plot. Each rectangular field represents an overlap of group membership, for instance being a member of both *adaptive* profiles across state conditions, and is proportional in size to the number of individuals in that cross-section.

Chi-square analyses revealed that profile membership and sex were not independent, for both the no choice condition, χ^2 (3, $N = 332$) = 8.83, $p = .032$, $\phi = 0.16$; and the choice condition, χ^2 (3, $N = 328$) = 9.17, $p = .027$, $\phi = 0.17$. The proportions of girls and boys in the *moderate* profile and the two negative profiles drove this dependency: Girls were more likely to be in the *moderate* profile than predicted and boys were more likely to be in both the *negEmo-lowerApp* and the *bored-*

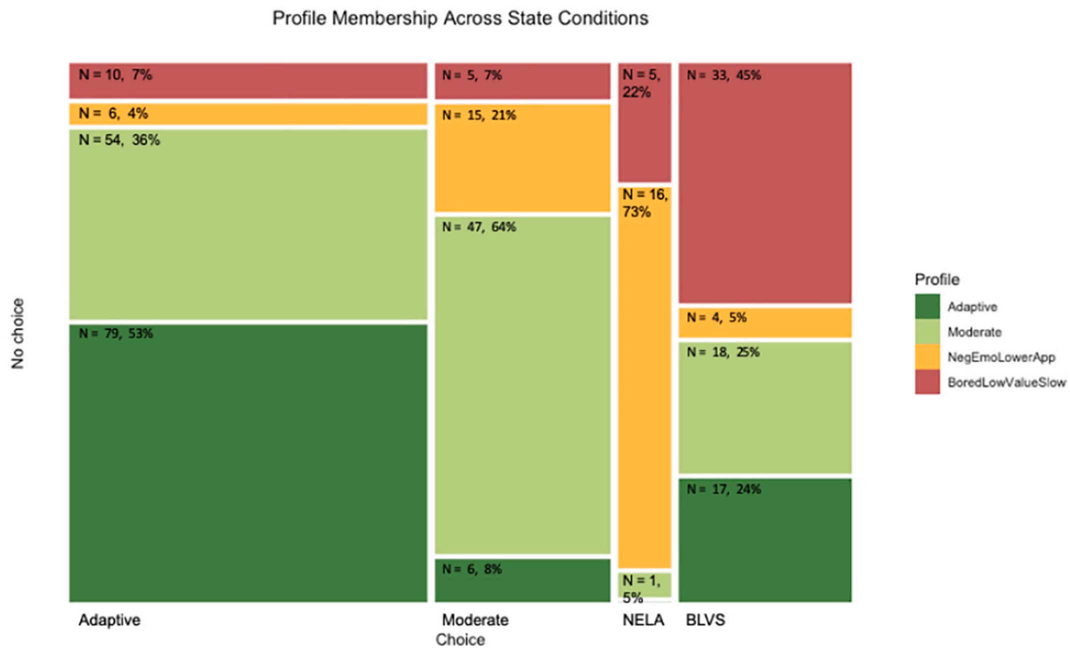

Fig. 4. Mosaic plot representing the distribution of profile membership across the four state conditions.
Note. The N-values and percentages denote how many individuals of each choice condition profile belong to each profile of the no choice condition. The colour of each rectangle corresponds to the profile an individual is in the *no choice* condition, contingent on their profile membership of the *choice* condition. The width of the rectangles corresponds to the proportion of individuals in each profile of the *choice* condition, whereas the height corresponds to the proportion of individuals in the *no choice* condition, contingent on the individual's membership in the *choice* condition. The third column, for instance, represents individuals in the *NegEmoLowerApp* profile of the *choice* condition (7%), making it quite narrow. Within that column, the yellow block has the greatest height, as 73% of individuals in the *NegEmoLowerApp* belong to the same profile in the *no choice* condition.
Abbreviations: NegEmoLowerApp, NELA = Negative emotion, lower appraisals profile; BoredLowValueSlow, BLVS = Bored, low value and slow profile. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

lowValue-slow profile than predicted.

3.3. Relation trait and state profiles

Lastly, we investigated the relation between trait and state profiles. Fig. 5 shows the distribution of learners across trait and state profiles in a mosaic plot, in which cross-sectional membership is represented in rectangular fields which are sized proportionally to the size of the cross-section. Membership in trait and state EAPs were not independent, χ^2 (3, $N = 323) = 21.21, p < .001, \phi = 0.26$ for the no choice condition, [χ^2 (3,

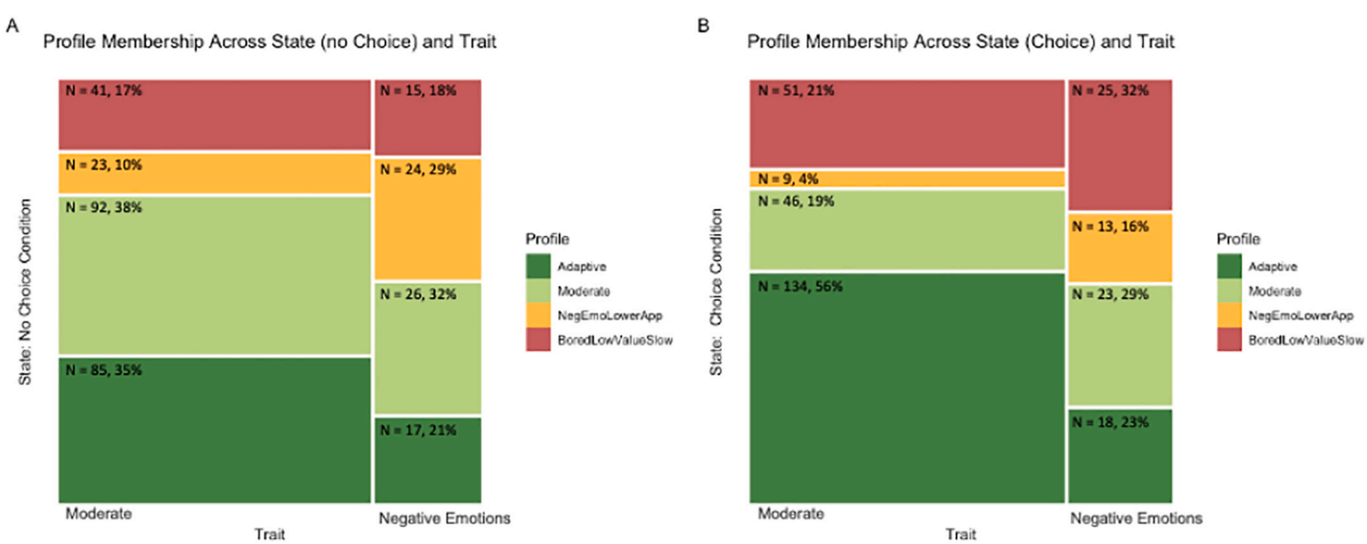

Fig. 5. Mosaic plots representing the distribution of profile membership across the trait level and the two state conditions: the no choice condition (panel A) and the choice condition (panel B).
Note. The width of the rectangles corresponds to the proportion of individuals in each trait profile, whereas the height corresponds to the proportion of individuals in the state profile, contingent on the individual's membership in the trait profile. The N-values and percentages denote how many individuals of the state profiles belong to each trait profile.
Abbreviations: NegEmoLowerApp = Negative emotion, lower appraisals profile; BoredLowValueSlow = Bored, and low value and slow profile. See the caption of Fig. 4 for a more thorough description of the plot.

$N = 319) = 32.95$, $p < .001$, $\phi = 0.32$ for the choice condition]. Concerning the no choice condition, those learners who belonged to the *moderate* trait profile were more likely to be in the *adaptive* and *moderate* state EAPs, whereas those learners belonging to the *maladaptive* trait profile were more likely to belong to the *negEmo-lowerApp* state EAP. Trait profile membership did not determine membership of the *bored-lowValue-slow* profile in the no choice condition. Concerning the choice condition, those learners who belonged to the *moderate* trait profile were more likely to be in the *adaptive* EAP profile, whereas those learners belonging to the *maladaptive* trait profile were more likely to belong to any of the other three state EAPs.

4. Discussion

The aim of the current study was to investigate EAP profiles, which may emerge on both the trait and the state level, due to the bidirectional relationships between emotions, appraisals and performance posited in the CV theory (e.g., Pekrun et al., 2017). Such profiles represent qualitative differences between groups of students (Hickendorff et al., 2018). In the following, we will first discuss our hypotheses in light of the findings of the current study, we will then shortly discuss theoretical and practical implications of our study before moving on to the limitations and a future outlook.

4.1. Main findings

Meaningful profiles emerged on both the trait and state level, confirming Hypothesis 1. Hypothesis 2, namely the emergence of three profiles on the trait level, was not supported, as only two profiles emerged on the trait level: A *maladaptive* profile with higher levels of negative emotions, lower levels of control and value appraisals and performance. In line with earlier findings, negative trait emotions co-occurred, in combination with low control and value appraisals and poor performance (e.g., Nett et al., 2017; Peixoto et al., 2017; Pekrun et al., 2011; Watson & Clark, 1992). The second and larger profile was a *moderate* profile with higher levels of enjoyment, control and value appraisals and performance. Contrary to our expectations and earlier findings in studies on trait emotion profiles, no adaptive profile emerged on the trait level, which may be due to weaker reciprocal effects for positive than negative emotion constructs (Pekrun et al., 2017).

Hypothesis 3, namely that state EAP profiles would differ based on the choice condition, was partly supported: Four similar profiles emerged across choice conditions, differing in their size and partially in their features. In both conditions, an *adaptive*, a *moderate*, a *negEmo-lowerApp* and a *bored-lowValue-slow* profile emerged. The *adaptive* profile is marked by low levels of negative emotions, high levels of enjoyment and control and value appraisals and short reaction times (i.e., high effort and/or ability) and the *moderate* profile is marked by moderate levels on all variables. With high levels on all three negative emotions, the *negEmo-lowerApp* profile is in accordance with earlier findings on the co-occurrence of similarly-valenced state emotions (e.g., Nett et al., 2017; Vansteelandt et al., 2005; Zelenski & Larsen, 2000) and combines long reaction times (in the no choice condition) with relatively low appraisals of control and value. The *bored-lowValue-slow* highlights that boredom does not necessarily have to co-occur with other negatively-valenced emotions. Our findings suggest if value is relatively lower in combination with relatively higher control, boredom may be the predominant emotion, confirming expectations of CV-theory - also given the long reaction times (i.e., low effort) (Pekrun, 2006): Boredom may be experienced in tasks lacking incentive value, but also in tasks without sufficient challenge (i.e., high control/low commands) and leads to lower effort. Contrary to Hypothesis 3.1, that profiles would be more extreme in the *no choice* condition, profile membership seemed to actually be more polarized in the *choice* condition: In the *choice* condition, more individuals belonged to the *adaptive* and the *bored-lowValue-slow* profile, whereas more individuals in the *no choice* condition belonged in the *moderate* and the *negEmo-lowerApp* profile. Due to higher control in the choice condition, the challenge may have been perceived as even less sufficient, leading to a larger boredom profile than in the no choice condition. Moreover, as expected (Hypothesis 3.2), due to the low task difficulty, anger and especially boredom were dominant, with levels of boredom being medium to high in all profiles, as were levels of task control. As such, boredom has been found to be a frequently experienced academic emotion (Mann & Robinson, 2009; Pekrun et al., 2010, 2014; Tze et al., 2016).

Hypothesis 4, namely that trait and state EAPs are related, was supported: Being in the *moderate* trait profile seemingly acted as a buffer for being in one of the two negative state profiles, whereas individuals belonging to the *negative* trait profile were more likely to also belong to one of the negative state profiles. In the choice condition, more than half of the individuals in the *moderate* trait profile belonged to the *adaptive* state profile, possibly suggesting that individuals with a more positive trait profile are sensitive to task context effects: When given more control within the task, they are likely to perform better on a task and enjoy it more than when given less control. The relation between trait and state EAPs supports the finding of trait level constructs being important determinants of what is experienced on the state level, but also that context is important (Nett et al., 2017). It should be noted that while the measures across levels do not align perfectly (see limitations section for a discussion of the issue) the EAP profiles based on the measures are still related, which is an interesting finding in itself.

Lastly, Hypothesis 5, namely that sex differences would be present in the number of individuals within the profiles, was supported, as sex differences were found on both the trait and the state level. We firstly expected that girls would be overrepresented in any EAPs marked by relatively high levels of anxiety and lower levels of control appraisals, especially on the trait level (Hypothesis 5.1). On the trait level, we found that girls were actually overrepresented in the *moderate* profile and not in the *negative emotions* profile, which had higher levels of anxiety, but also of anger and boredom. On the state level, girls were overrepresented in the *moderate* profile, which did have relatively high levels of anxiety. As such, our results are in slight contrast to earlier results showing that girls have higher math trait anxiety but not state anxiety than boys (Bieg et al., 2015; Goetz et al., 2013), but these studies looked at mean level differences, and not patterns of associations of variables within subgroups of learners. Moreover, differences in math anxiety on the state level were found in a recent study (Orbach et al., 2019). Secondly, we expected that boys would be overrepresented in any EAPs marked by higher levels of boredom (Hypothesis 5.2). On the both the trait and the state level, boys were indeed overrepresented in the profiles marked by higher levels of boredom: in the *negative emotion* profile on the trait level and in both negative state profiles across choice conditions, in line with research showing that boys experience more boredom than girls (Pekrun et al., 2010, 2017). It should be noted that in earlier studies on state emotion profiles, no sex differences were found (Robinson et al., 2017; Tulis & Ainley, 2011), which might indicate that the inclusion of appraisals and performance lead to our finding of sex differences.

4.2. Theoretical implications

Our finding of meaningful EAP profiles emerging on the trait and state level highlight the importance of considering the existence of subgroups of learners having qualitatively different patterns of relations of emotions, appraisals and performance. Such profiles are in line with the predictions of control-value theory of couplings of emotions, appraisals of control and value and performance (e.g., Pekrun, 2006; Pekrun et al., 2011):Due to bidirectional couplings, some individuals may experience positive emotions, high levels of control and value and perform well, while others may express an opposing pattern. The emergent profiles did not display the fine-grained assumptions of CV-theory, in which the interaction of control and value appraisals is thought to lead to distinct emotions (leading to one EAP per emotion). Instead, we replicated earlier findings on the co-occurrence of similarly valence emotions (e.g., Nett et al., 2017; Peixoto et al., 2017; Pekrun et al., 2011; Watson & Clark, 1992) and found that state EAPs seem to be more differentiated than trait EAPs - which may be due to trait assessments being more biased by selective recall and subjective beliefs (Robinson & Clore, 2002).

4.3. Practical implications

Knowing of the existence of qualitatively different subgroups of learners based on their emotions, appraisals and performance has various practical implications which may aid the development of interventions aimed at facilitating adaptive emotions and performance. First, while no adaptive trait EAP profile emerged, aiding students to develop even a moderate trait EAP seems to be adaptive: Students in such a profile have higher grades and are more likely to be in a more adaptive EAP on the state level. The context of the task also had an important effect on this group of students: providing them with higher levels of task control led to a majority of them being in the *adaptive* EAP. Students in the maladaptive trait EAP seem to have particularly high levels of anger and boredom and low levels of intrinsic value. With appraisals of control and value being malleable constructs (e.g., Aronson & Steele, 2005; Magidson et al., 2014; Vrugt et al., 1997) an intervention focusing on increasing their appraisal of value of mathematics may be beneficial for students in this subgroup, especially so as increased value appraisals may lead to experiencing less anger and boredom (Pekrun, 2006).

Giving learners the opportunity to choose the difficulty level of items seems to polarize learners' experiences, as a larger number of students belonged to the *adaptive* EAP but also a larger number of students belonged to the *bored-low value-slow* EAP in the *choice* condition than in the *no choice* condition. So while giving a choice might have made the experience less challenging and more boring for some learners, it improved the learning experience for others - highlighting the importance of taking individual differences into account when designing learning experiences. This is in line with earlier findings, showing for instance, that only learners with an initial sense of competence benefit from having a choice (e.g., Patall et al., 2014).

4.4. Limitations and future research

The results of the current study should be interpreted with care, considering the following limitations. First and foremost, the task at hand was aiming to manipulate learners' task value and control appraisals, a manipulation that failed. Given the ceiling effect on accuracy, we were unable to include accuracy as a measure of performance, but used reaction times on correctly solved items as an indicator of performance/effort, a measure which is not as straightforward to interpret as accuracy would have been. Using a more difficult math task presents an avenue for future research – performance may then be a more important factor in determining learners' state EAP profiles. Moreover, care should be taken when selecting measures - especially when comparison across the trait and state level is desired: While using shorter scales on the state than the trait level is appropriate (Gogol et al., 2014), the comparability of measures could be increased by using measures of, for instance, utility value on both the state and the trait level. Future studies are needed to test whether using more similar measures across levels changes the dependency of membership of EAPs across levels.

Next, we relied on self-reported math grade for an indication of performance on the trait level. Self-reported mathematics grades and actual grades have been found to be highly positively correlated (Sticca et al., 2017). Although studies have found that especially students with lower grade point averages may overreport their grades (Schwartz & Beaver, 2015), the tendency to overreport grades has a small effect size (Cohen's $d = 0.16$). Kuncel et al. (2005) argue that self-reported grades can be used with caution, especially so when the findings mirror those of studies using school-reported grades (i.e., higher grades are related with higher levels of enjoyment); which is the case in the current study. Future studies using actual grades (obtained by the school) are needed to replicate the current results.

When interpreting the current findings, one should keep in mind that the sample only concerned Dutch secondary school students from the two highest tiers of the school system. Dutch teenagers have lower levels of math self-efficacy and extrinsic motivation for math but score significantly higher on math self-concept and mathematics intentions than students of other OECD countries (Kordes et al., 2013). Moreover, levels of math anxiety have been shown to be lower in the Netherlands than in other countries (Lee, 2009). Future research is needed to disentangle the effects of different learning contexts, culture, school level, age and sex on mathematics learning profiles, especially so as we could not account for possible measurement invariance in the current study.

Lastly, we have followed the standard three-step approach to test whether the covariance gender is related to profile membership (see Hickendorff et al., 2018). Each individual was thus assigned to their most likely class based on their posterior probabilities, introducing error to the analysis (Bolck, Croon, Hagenaars, 2004; Bray et al., 2015). In future studies, a bias-adjusted three-step analysis should be applied, in which profile membership is weighted by the classification error (e.g., Asparouhov & Muthén, 2014, Bray et al., 2015).

An interesting avenue for future research is whether profile membership can be affected – and how. Increasing students' appraisals of control and value for mathematics, for instance, could result in the development of a more positive profile. But theoretically speaking, such a positive development may also be attained by helping learners to achieve better – or by increasing the enjoyment they experience in relation to math. Such research should be done using cross-sectional, or, preferably, longitudinal data. Longitudinal studies may also shed light on the development of learning profiles over time.

4.5. Conclusion

Looking beyond mean level differences of pre-defined groups (e.g., boys and girls), on emotion, appraisals, and performance, allowed us to identify latent groups of learners who are qualitatively different in their *patterns* of relations of emotions, appraisals and performance - both on the trait and state level. On a trait level, this resulted in two learning profiles, a moderate one and a negative emotion one. The learners belonging to the negative emotion profile experienced more negative emotions paired with less positive appraisals and enjoyment as well as performance – highlighting that teachers should strive to prevent the development of such negative mathematics learning profiles. On a state level, a more fine-grained picture emerged, as four profiles were identified – which differed slightly based on the situation. In sum, the use of a person-centered approach allowed us to include emotions, appraisals, and performance, and to represent their pattern of associations in a more complete manner.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2021.102029.

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