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Exploring students' receptivity to feedback: A latent profile analysis

J. Luca Bahr[a], Lars Höft[a], Anastasiya Lipnevich[b], Jennifer Meyer[a] and Thorben Jansen[a]

[a]Leibniz Institute for Science and Mathematics Education, Kiel, Germany; [b]Queens College and the Graduate Center, City University of New York, New York, USA

ABSTRACT

A comprehensive understanding of why feedback benefits some students and not others is still lacking. We performed latent profile analysis of students' receptivity to instructional feedback (RIF) in a sample of 1800 secondary school students from Germany (age: $M = 16.37$, $SD = 1.47$). We described RIF profiles, predicted profile membership using established factors (cognitive ability, personality traits, prior achievement, age, and gender) that relate to feedback uptake, and examined how profile membership related to revision performance in writing. We identified three profiles distinguished by behavioral, and cognitive engagement with feedback, experiential, and instrumental attitudes towards feedback, and overall receptivity to feedback: *Indifferent Nonresponders*, *Empty Promisers*, and *Committed Realists*. The least successful profile was associated with having lower indicators of cognitive ability and agreeableness and higher neuroticism. We discuss these findings in light of the benefits of a person-centred approach compared to a variable-centred approach often used in past research.

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Feedback; receptivity to instructional feedback; latent profile analysis; individual differences; personality

Feedback can play a pivotal role in performance and learning, but its effectiveness varies greatly among students (Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Wisniewski et al., 2020). Given that feedback can only be beneficial if students engage with it (Lipnevich & Smith, 2022; Lipnevich et al., 2016; Murano et al., 2021), extensive research has been devoted to understanding factors that influence students' receptivity to feedback, emphasising the key role of student characteristics in feedback effectiveness (Panadero & Lipnevich, 2022; Winstone et al., 2022). However, a comprehensive understanding of characteristics that contribute most to students' effective feedback uptake is still lacking (Winstone & Nash, 2023). Hence, scholars have been calling for research on how student individual differences influence feedback processing. Such research is essential to explain the variability of findings on feedback effectiveness and to develop adaptive pedagogical approaches and scalable interventions (e.g. Panadero, 2023).

CONTACT J. Luca Bahr bahr@leibniz-ipn.de Leibniz Institute for Science and Mathematics Education, Olshausenstraße 62, Kiel 24118, Germany

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In their comprehensive review article, Panadero and Lipnevich (2022) identified several student characteristics (e.g. cognitive ability, personality traits, age, gender, and prior knowledge) that shape students' reception and agentic use of feedback. Individual differences in feedback reception, termed receptivity to instructional feedback (RIF), capture students' trait-level tendencies to accept feedback (Lipnevich et al., 2021). The construct comprises students' behavioral ('Do I know what to do with feedback?') and cognitive ('Do I understand feedback?') engagement with feedback, their instrumental ('Do I think feedback is useful?') and experiential ('Do I like feedback?') attitudes towards receiving feedback, as well as their overall ('Am I willing and ready to accept feedback?') receptivity to feedback (Bahr et al., 2024; Lipnevich et al., 2021). Earlier research on this multidimensional construct has solely focused on variable-centred approaches (Bahr et al., 2024; Lipnevich & Lopera-Oquendo, 2022; Lipnevich et al., 2021), however, varying levels on RIF dimensions that students exhibit may not operate independently and must therefore be considered jointly. For instance, a student might value (instrumental attitudes) and enjoy (experiential attitudes) receiving feedback but still struggle with the implementation (behavioral engagement) of it. Thus, complementing a variable-centred approach with a more person-centred approach that allows for the consideration of multiple variables could enhance our understanding of why some students accept and engage with feedback more effectively than others.

Therefore, the aim of this study was to provide a holistic representation of RIF profiles by 1) identifying and characterising RIF profiles, 2) identifying differences in profile membership based on cognitive ability, personality traits, prior achievement, age, and gender, and 3) exploring the links between different RIF profiles and revisions on a writing task (see Jansen et al., 2025; Steegh et al., 2021, for similar approaches and best practice examples).

Profile defining construct: dimensions of receptivity to instructional feedback (RIF)

The RIF construct has its origins in personality psychology and can be described as trait-like feedback receptivity (Lipnevich & Lopera-Oquendo, 2022). It is based on the underlying idea that individuals can differ in their willingness and capability to receive feedback (Lipnevich et al., 2016). For instance, some students might welcome feedback across academic situations, whereas others may not be as open to it (Lipnevich & Lopera-Oquendo, 2022).

Regarding the associations of RIF with student learning outcomes, studies have shown that students' general receptivity to feedback, their behavioral and cognitive engagement with feedback, and their experiential attitudes towards feedback related to students' grades (e.g. grade point average [GPA]; Bahr et al., 2024; Lipnevich & Lopera-Oquendo, 2022). Given that feedback receptivity is a complex and intertwined phenomenon, exploring other established cognitive and non-cognitive factors that relate to feedback effectiveness could help to explain differences in students' feedback receptivity profiles.

Predictors of profile membership

In order to better understand differences in membership of the receptivity profiles, associations with other established individual characteristics (i.e. cognitive ability, personality traits, prior achievement, age, and gender) that relate to feedback uptake and achievement in school must be investigated (Panadero & Lipnevich, 2022). Both cognitive ability (D. Luo et al., 2006; Roth et al., 2015) and personality traits (Mammadov, 2022; Meyer et al., 2023, 2024; Poropat, 2009), especially conscientiousness, are among the well-established predictors of school achievement, and can be hypothesised to predict RIF as well (Panadero & Lipnevich, 2022). Although a few studies have investigated the association of RIF with personality traits in variable-centred approaches (Bahr et al., 2024; Lipnevich et al., 2021), there remains a gap in the literature regarding cognitive ability and its link to RIF. Notably, Lipnevich et al. (2021) showed that conscientiousness and openness were strong predictors of the four RIF sub-dimensions, while Bahr et al. (2024) highlighted the strong association between general receptivity and conscientiousness, with moderate to large associations with openness.

Further, students' prior school achievement, such as GPA, might play a role in their receptivity to feedback, as prior knowledge or performance has been linked with the agentic use of feedback (Panadero & Lipnevich, 2022). Moreover, gender has been found to relate to students' effective feedback uptake. Specifically, female students tend to benefit more from feedback in computer-based assessment contexts (Narciss et al., 2014, Timmers et al., 2015). Similarly, Lipnevich and Lopera-Oquendo (2022) found that girls scored higher on RIF subscales, indicating greater receptivity to feedback. Age-related differences can also impact how students react to feedback. Research in industrial and organisational psychology has revealed age-related variability in individuals' reactions to feedback (Wang et al., 2014). Accordingly, these demographic variables might also be related to students' RIF and provide new explanations for why some students are more accepting of feedback than others. Understanding these factors could help educators tailor feedback strategies to meet the diverse needs of their students, thereby enhancing overall feedback effectiveness.

Present study

In this study, we aimed to identify and characterise RIF profiles in order to investigate how profile membership was predicted by cognitive ability, personality traits, prior achievement, age, and gender, and to explore links between different RIF profiles and students' revision performance in writing. To this end, we performed latent profile analysis to answer the following research questions:

(1) How do general receptivity, behavioral engagement with feedback, cognitive engagement with feedback, experiential attitudes towards receiving feedback, and instrumental attitudes towards receiving feedback define RIF profiles in secondary school students?
(2) How do cognitive ability, personality traits, prior achievement, age, and gender predict differences in profile membership?

(3) How does profile membership predict revision performance in an argumentative writing task?

We conducted our study in the context of socioscientific argumentative writing, which is an educational priority in German K-12 education, as it integrates all components of the educational standards for the natural sciences and prepares students for meaningful participation in societal discourse (KMK, 2020; Osborne & Pimentel, 2022; Parchmann & Kuhn, 2018; Weiss et al., 2015). Despite this importance, many students have difficulties in argumentative writing (Keller et al., 2020, 2024; Stanat et al., 2023). By focusing on this critical area, we aimed to provide insights into how feedback can be effectively utilised to enhance students' argumentative writing skills and overall academic performance.

Method

Open science

We confirm that there is sufficient information for an independent researcher to reproduce all of the reported methodology. The data and code are available at https://osf.io/ayske .The study is a secondary data analysis within a larger project. The analyses were not preregistered. The Ethics and Data Protection Commission Leibniz Institute for Science and Mathematics Education in Kiel, Germany reviewed the study.

Design and sample

1800 students (age: $M = 16.37$, $SD = 1.47$, range = [14, 21], 17.2% missing; gender: 42.8% females, 36.2% males, 4.4% other, 16.7% missing) from academic secondary schools (equivalent to high schools; 'Gymnasium' in Germany, $n = 1{,}207$) and nonacademic secondary schools (equivalent to comprehensive schools; 'Gemeinschaftschule' in Germany, $n = 593$) in Germany participated.

In Germany, both the 'Gymnasium' and 'Gemeinschaftsschule' are publicly funded schools. However, they have different educational missions and pedagogical approaches. The 'Gymnasium' is known for being highly selective and focuses on preparing students specifically for university education. Students who graduate from a 'Gymnasium' receive the general higher education entrance qualification. On the other hand, the 'Gemeinschaftsschule' offers a more flexible education path where students can earn various qualifications, ranging from basic school-leaving certificates to the general higher education entrance qualification. The inclusion of students from both 'Gymnasium' and 'Gemeinschaftsschule' offers a broader understanding of how diverse educational contexts affect students in Germany.

Procedure

The study was conducted in students' usual classrooms during regular class time and all materials were provided within a digital learning environment accessed through standard web browsers. Parental consent forms for study participation were collected.

Data on students' grade level was collected and their cognitive abilities were measured through a grade-appropriate assessment. Then, students were asked to complete the RIF questionnaire. After that, the participants received their writing task. The task required them to write an argumentative essay on one of two climate change topics, advocating one of the three options listed in each topic for possible policy support (see Table S1, Supplementary Material). Moreover, students were provided with four key 'hints for very good argumentation' to guide their writing process. These hints served a tripartite function: firstly, to scaffold and enhance the quality of students' writing; secondly, to establish a clear metric for assessing task performance; and thirdly, to provide a structured foundation for the subsequent feedback they would receive (see Table S1, Supplementary Material). The topic of the task was assigned randomly.Students had fifteen minutes to write a draft and were provided with information in favour of and arguments against each of the three options. After having written their first draft, students were given one out of four predefined computer-based feedback messages, each addressing one of the four tips on how to write a good text (see Table S2, Supplementary Material). Then, students had ten minutes to revise their texts based upon the feedback they received. At the end, students were asked to provide demographic data (personality traits, school track, age, GPA, and gender).

Instrumentation

Receptivity to instructional feedback

The RIF scale is a self-report instrument intended to measure students' acceptance of instructional feedback (Bahr et al., 2024; Lipnevich et al., 2021). In computer-based assessment contexts the scale contains 18 items and is best conceptualised with a bifactor-CFA model, which can capture the latent construct of general receptivity (Bahr et al., 2024). This modelling approach delineates the variance in item responses into a general factor (G-factor, i.e. general receptivity), representing the overall receptivity not tied to any specific dimension, and specific factors (S-factors), which account for variance attributable to each of the four predefined subscales. The instrument comprises a behavioral engagement subscale (6 items, e.g. 'I work through the feedback I receive'), a cognitive engagement subscale (4 items, e.g. 'I understand how to use feedback to make my work better'), an experiential attitudes subscale (5 items, e.g. 'I look forward to receiving feedback on my work'), and an instrumental attitudes subscale (3 items, e.g. 'Feedback is important for my success'). The items are measured on a five-point Likert scale from *strongly disagree* (1), *disagree* (2), *neither* (3), *agree* (4), to *strongly agree* (5). Reliabilities are presented in Table 1.

Cognitive ability

We measured students' cognitive abilities utilising the non-verbal figural analogies' subscale of a cognitive abilities test (KFT-R; Heller & Perleth, 2000) and applied a multi-group IRT model to estimate WLE scores representing students' general cognitive ability score (EAP/PV reliability = .84, WLE reliability = .79) on the same metric.

Table 1. Means, standard deviations, reliabilities, and latent correlations of variables.

Measure	*M*	*SD*	*α*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. School track	0.67	0.47																
2. Gender	1.45	0.50		−.01														
3. Age	16.37	1.47		−.33***	.02													
4. Behavioral	3.17	0.89	.85	.05*	−.10***	−.02												
5. Cognitive	3.67	0.75	.81	.02	.00	−.02	.46***											
6. Experiential	3.95	0.79	.79	.05*	−.01	.00	.39***	.33***										
7. Instrumental	3.66	0.87	.75	−.02	−.06*	.04	.57***	.48***	.44***									
8. Agreeableness	2.88	0.77	.57	.01	−.07*	.04	.12***	.03	.12***	.17***								
9. Extraversion	3.23	0.89	.75	−.04	−.02	.04	.04	.11***	.12***	.08**	.07**							
10. Conscientiousness	3.32	0.73	.66	.01	−.22***	.01	.37***	.29***	.22***	.28***	.09**	.14***						
11. Neuroticism	3.18	0.90	.74	.00	−.32***	−.03	−.01	−.18***	−.13***	−.02	−.05	−.27***	−.03					
12. Openness	3.64	0.75	.67	.02	−.19***	.01	.24***	.16***	.10***	.19***	.04	.11***	.20***	.17***				
13.Cognitive ability	0.00	1.00	.79	.26***	.08**	.01	.05*	.10***	.18***	.05*	−.09***	−.07**	−.03	−.02	.10***			
14. GPA	9.74	2.52		.17***	−.06*	−.19***	.15***	.18***	.18***	.13***	−.01	.10***	.30***	−.06*	.07*	.25***		
15.Draft performance	−0.03	0.77		.12***	−.06*	−.06*	.06*	.10***	.12***	.08**	−.03	−.02	.05	.02	.02	.18***	.09***	
16.Revision performance	0.16	0.82		.09***	−.09**	−.02	.10***	.12***	.15***	.11***	−.05	−.05	.11***	.06*	.09***	.22***	.11***	.74***

*$p < .05$; **$p < .01$; ***$p < .001$.

Big five personality

The Big Five dimensions of personality were measured with the 21-item inventory (Rammstedt & John, 2005): agreeableness (4 items), conscientiousness (4 items), extraversion (4 items), neuroticism (4 items), and openness (5 items). All items were assessed on a five-point scale from *strongly disagree* (1), *disagree* (2), *neither* (3), *agree* (4), to *strongly agree* (5). The scale reliability estimates of the present study (see Table 1) are similar to those reported in the initial validation studies (Kovaleva et al., 2013; Rammstedt & John, 2005).

Other variables

We included students' gender[1] (0 = male, 1 = female), age, GPA, and school track (0 = nonacademic, 1 = academic).

Revision performance change

Revision performance change from T1 to T2 was calculated using latent change score modelling (CFI = .995, TLI = .995, RMSEA = .061, SRMR = .049; see Schaller et al., 2024 for the text annotation process, and Jansen et al., 2025 for the scoring procedure and reliability).

Analytic plan

All analyses were conducted in MPlus 8.7 (Muthén & Muthén, 1998-2017) with non-normality robust standard errors using the MLR estimator (Asparouhov & Muthén, 2005). The overall model fit for the bifactor-CFA model was evaluated using common fit indices (Browne & Cudeck, 1992; Hu & Bentler, 1999). For our first research question, the identification of profile membership was determined using latent profile analysis. In line with the methods proposed by Marsh et al. (2009), we did not restrict the variances and set the residual covariances to zero. To determine the ideal number of profiles, we relied on the Akaike information criteria (AIC), Bayesian information criteria (BIC), and sample-size adjusted BIC (saBIC).Lower AIC, BIC, and saBIC values indicate better model fit. Moreover, we used the Lo – Mendell – Rubin likelihood ratio test (LMR) for model comparison. A significant outcome on the LMR indicates a superior model fit in comparison to a model with one fewer profile. Also, we assessed classification accuracy with the model entropy (with values ranging between 0 and 1). A model with higher entropy is indicative of a more accurate classification of individual cases into profiles (Clark & Muthén, 2009). Among the aforementioned criteria, BIC, aBIC, and LMR were given more weight, as AIC and entropy were deemed less effective for choosing the best profile solutions (Tein et al., 2013).

To address our second research question (i.e. predicting profile membership by cognitive ability, personality traits, prior achievement, age and gender), we used a modified three-step approach developed by Vermunt (2010), which comprises the following three steps: 1) estimation of the latent profile model using only indicator values, 2) classification of participants based on the highest probability of profile membership, 3) multinomial logistic regression of the most likely profile of participants (as a nominal variable) on the predictors. In the third step of the procedure, the classification

error probabilities were taken into account as the nominal variables were linked to the latent profiles.

Finally, for our third research question, we used the Bolck-Croon-Hagenaars (BCH) method to examine how profile membership predicted revision performance (Bakk & Vermunt, 2016). Specifically, we conducted equality tests that compared the average score of participants per profile across all latent profiles (Bakk & Vermunt, 2016). The BCH approach also consisted of three steps, similar to the three-step approach developed by Vermunt (2010). The main advantage of the BCH approach is that it applies an analysis of variance that calculates individual weights in the third step of the method, which were used as an imperfect latent profile indicator instead of the modal profile assignment (nominal variable).

Results

Means, standard deviations, reliabilities, and intercorrelations of all variables are summarised in Table 1. The bi-factor CFA model demonstrated a good fit to the data ($\chi 2(117, N = 1800) = 643.47$, $p < .001$; *RMSEA* = .050; *CFI* = .944; *TLI* = .927; *SRMR*= .032).

Model fit indices for the different profile solutions are set out in Table 2. The AIC and BIC decreased consistently from one-profile to the five-profile solution, suggesting better fit with more profiles. Similar to AIC and BIC, saBIC also decreased as the number of profiles increased. Entropy increased from 0.60 in the two-profile solution to 0.70 in the four-profile solution, indicating improved classification. However, it slightly decreased in the five-profile solution. LMR was significant for two- and three-profile solutions, suggesting these were better than their previous iterations (one- and two-profile solutions, respectively). It was no longer significant from the four- to five-profile solutions, indicating that adding more profiles did not significantly improve model fit. In addition, the four-profile and five-profile solutions had very small classes ($N = 15$ and $N = 11$, respectively). Considering these indices, the three-profile solution emerged as the most balanced choice. It achieved a good balance between model fit (as indicated by decreases in AIC, BIC, saBIC), classification clarity (higher entropy), and meaningful class sizes, while showing significant improvement over the two-profile solution according to the LMR test. Adding more profiles would have complicated the model without substantial improvement in fit, as indicated by non-significant LMR values and extremely small class sizes. Thus, the three-profile model was considered optimal.

Figure 1 illustrates the mean scores per profile for the three-profile solution (see Figure S1 for a line graph depicting the mean scores of the different profile solutions investigated, Supplementary Material). We labelled the profiles *Indifferent*

Table 2. Model fit indices for different profile solutions.

Model	AIC	BIC	saBIC	Entropy	LMR	Profile sizes
1 profile	20501.76	20556.72	20524.95			1800
2 profiles	19641.83	19757.24	19690.52	0.60	<.001	898; 902
3 profiles	**19411.03**	**19586.89**	**19485.23**	**0.65**	**< .001**	**771; 359; 670**
4 profiles	19155.79	19392.10	19255.49	0.70	.208	466; 719; 600; 15
5 profiles	18992.39	19289.15	19117.59	0.69	.057	393; 385; 328; 683; 11

The selected model is indicated by a **bold** font. AIC = Akaike information criteria; BIC = Bayesian information criteria; saBIC = sample-size adjusted BIC; LMR = p-value of Lo–Mendell–Rubin likelihood ratio test.

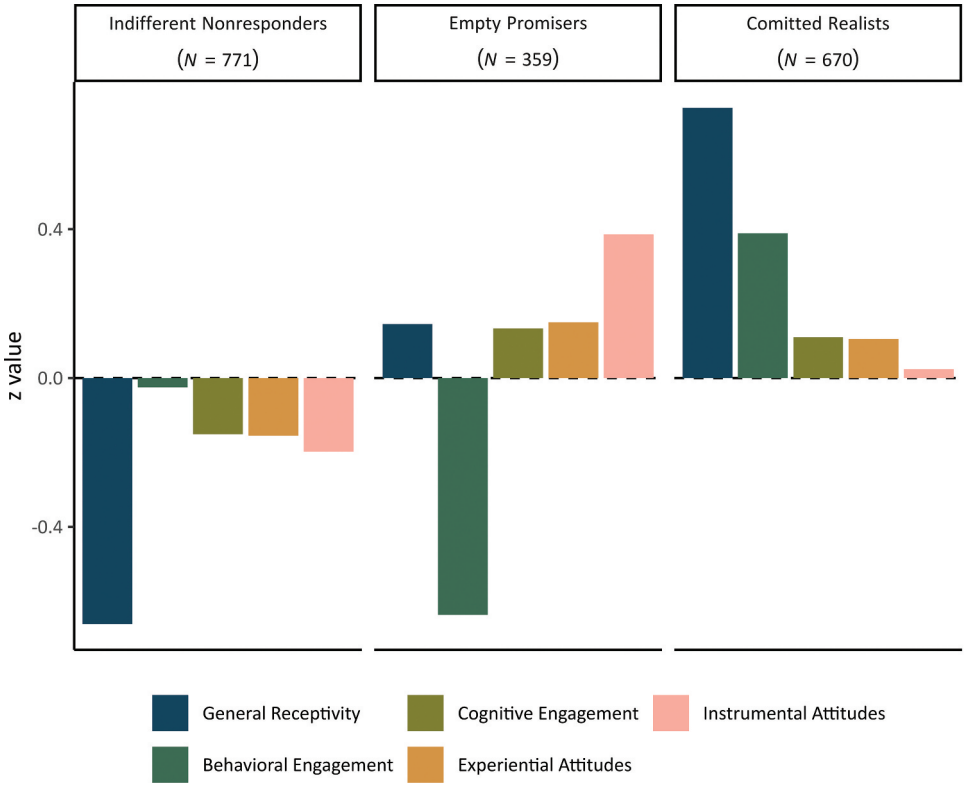

Figure 1. Z-standardized mean scores per profile for the three-profile solution.

Nonresponders ($N = 771$), *Empty Promisers* ($N = 359$), and *Committed Realists* ($N = 670$). The *Indifferent Nonresponders* showed low behavioral and cognitive engagement and held low experiential and instrumental attitudes towards receiving feedback. In contrast, the *Committed Realists* showed high levels on all receptivity dimensions. Students associated with the *Empty Promisers* profile showed low behavioral engagement, along with average global receptivity and cognitive engagement, and held average experiential and instrumental attitudes towards receiving feedback.

In order to answer our second research question, the results of the multinomial logistic regressions assessing the effects of the predictor variables on profile membership are displayed in Table 3. Compared to students associated with the *Indifferent Nonresponders* profile, those categorised into the *Empty Promisers* and *Committed Realists* profiles had a higher probability of having greater cognitive ability and being more agreeable and less neurotic. Furthermore, those in the *Empty Promisers* profile had higher chances of being older and more extraverted than those in the *Indifferent Nonresponders* profile. Students categorised into the *Committed Realists* profile had a higher chance of being more open and conscientious than those in the *Indifferent Nonresponders* profile. Compared to those in the *Empty Promisers* profile, those in the *Committed Realists* profile were less likely to be extraverted and more likely to be open and conscientious. School track, gender, and GPA were not associated with profile membership.

Table 3. Results of multinomial logistic regressions for the effects of predictors on profile membership.

Model	Non-reference profiles			
	Indifferent Nonresponders		*Empty Promisers*	
	Est. [95% CI]	OR [95% CI]	Est. [95% CI]	OR [95% CI]
Reference profile *Empty Promisers*				
School track	−0.01 [−0.42, 0.41]	0.99 [0.66, 1.51]		
Gender	−0.01 [−0.25, 0.23]	0.99 [0.78, 1.26]		
Age	**-0.22 [−0.42, −0.02]**	**0.81 [0.66, 0.98]**		
Cognitive ability	**-0.31 [−0.48, −0.14]**	**0.73 [0.62, 0.87]**		
GPA	−0.12 [−0.38, 0.14]	0.89 [0.68, 1.15]		
Agreeableness	**-0.31 [−0.58, −0.05]**	**0.73 [0.56, 0.95]**		
Conscientiousness	−0.26 [−0.52, 0.01]	0.77 [0.60, 1.01]		
Extraversion	**-0.35 [−0.66, −0.04]**	**0.71 [0.52, 0.97]**		
Neuroticism	**0.30 [0.01, 0.59]**	**1.35 [1.01, 1.81]**		
Openness	−0.24 [−0.49, 0.01]	0.79 [0.61, 1.01]		
Reference profile *Committed Realists*				
School track	−0.12 [−0.55, 0.31]	0.89 [0.58, 1.36]	−0.11 [−0.55, 0.32]	0.89 [0.58, 1.38]
Gender	0.11 [−0.09, 0.32]	1.12 [0.92, 1.37]	0.12 [−0.13, 0.38]	1.13 [0.88, 1.46]
Age	−0.06 [−0.28, 0.17]	0.95 [0.76, 1.18]	0.16 [−0.06, 0.38]	1.17 [0.94, 1.46]
Cognitive ability	−0.27 [−0.42, −0.12]	0.76 [0.66, 0.88]	0.04 [−0.13, 0.21]	1.04 [0.88, 1.23]
GPA	−0.12 [−0.32, 0.08]	0.89 [0.73, 1.08]	−0.00 [−0.25, 0.24]	1.00 [0.78, 1.27]
Agreeableness	−0.26 [−0.46, −0.05]	0.78 [0.63, 0.96]	0.06 [−0.16, 0.28]	1.06 [0.85, 1.32]
Conscientiousness	**-1.08 [−1.33, −0.83]**	**0.34 [0.27, 0.44]**	**-0.82 [−1.08, −0.56]**	**0.44 [0.34, 0.57]**
Extraversion	−0.03 [−0.22, 0.16]	0.97 [0.81, 1.18]	**0.32 [0.07, 0.57]**	**1.376 [1.07, 1.77]**
Neuroticism	0.48 [0.25, 0.70]	1.61 [1.28, 2.02]	0.18 [−0.08, 0.43]	1.19 [0.93, 1.54]
Openness	**-0.50 [−0.71, −0.29]**	**0.61 [0.49, 0.75]**	**-0.26 [−0.48, −0.04]**	**0.77 [0.62, 0.96]**

Est. = Logistic regression coefficient. These coefficients are in logit form and have to be interpreted as partial regression coefficients, adjusted for all other effects in the model; OR = odds ratios. Statistical significance is indicated by a **bold** font.

Regarding our third research question, the BCH method revealed significant differences in revision performance as an outcome of profile membership. Students categorised into the *Committed Realists* (*Intercept* = 0.070, *SE* = 0.037; *Difference* = 0.261, *SE* = 0.058, $p < .001$) and *Empty Promisers* (*Intercept* = −0.035, *SE* = 0.068; *Difference* = 0.155, *SE* = 0.077, $p = .045$) profiles had a significantly higher draft performance than students associated with the *Indifferent Nonresponders*(*Intercept* = −0.191, *SE* = 0.047) profile (omnibus-test: $\chi 2 = 20.19$, $p < .001$). Even after controlling for students' draft scores, the revision performance of students in the *Committed Realists* (*Intercept* = 0.246, *SE* = 0.026; *Difference* = 0.100, *SE* = 0.034, $p = .003$) and *Empty Promisers* (*Intercept* = 0.252, *SE* = 0.039; *Difference* = 0.106, *SE* = 0.046, $p = .021$) profiles were significantly higher than that of students associated with the *Indifferent Nonresponders* (*Intercept* = 0.146, *SE* = 0.023) profile (omnibus-test: $\chi 2 = 11.90$, $p = .003$).

Discussion

The purpose of this study was threefold. First, we aimed to identify and characterise RIF profiles. Second, we examined differences in profile membership based on students' cognitive ability, personality traits, prior achievement, age, and gender. Third, we explored the links between different RIF profiles and revisions made on a writing task.

In addressing our primary research question, we discovered distinct patterns in student feedback receptivity. One profile emerged with *Indifferent Nonresponders* showing a clear reluctance towards feedback. However, what caught our attention were the two additional profiles that we identified. Instead of a simple division between average and highly receptive students, we found a more intricate picture. Students in both groups reported relatively high levels of general receptivity, cognitive engagement as well as experiential and instrumental attitudes towards receiving feedback, but they differed with regard to their reported behavioral engagement with feedback. *Empty Promisers* were characterised by low levels of behavioral engagement whereas *Committed Realists* had high levels of behavioral engagement. This finding underscores the limitations of traditional approaches and emphasises the need to consider individual differences in feedback reception among students.

In addressing our second research question, we discovered compelling associations between certain individual characteristics and feedback receptivity profiles. Specifically, we found that individuals with higher cognitive ability, agreeableness, and lower neuroticism were more likely to belong to the *Committed Realists* and *Empty Promisers* profiles, which exhibited higher levels of feedback receptivity. Given that neuroticism is tied to increased sensitivity to criticism (e.g. Brockner et al., 1987; Servaas et al., 2013), it is reasonable to assume that students high in neuroticism might doubt their ability to implement feedback effectively. This lack of confidence can subsequently impair their willingness to engage with and make use of the feedback they receive, hence predicting membership in the least receptive profile, *Indifferent Nonresponders*. Further, it is not surprising that higher cognitive ability and agreeableness were associated with the more feedback receptive profiles *Committed Realists* and *Empty Promisers*, given their strong ties with academic achievement (e.g. Meyer et al., 2023, 2024). Moreover, higher cognitive ability, which is related to working memory capacity, has been shown to be beneficial to feedback processing (Fyfe et al., 2015), underpinning its predictive value for the *Committed Realists* and *Empty Promisers* profiles. Our findings complement previous research conducted using variable-centred approaches, highlighting the importance of cooperative and trusting dispositions (high agreeableness) in fostering feedback receptivity among students, as observed in the *Committed Realists* and *Empty Promisers* profiles (Bahr et al., 2024; Lipnevich et al., 2021).

Students categorised into the *Empty Promisers* profile were more likely to be extraverted and less likely to be open and conscientious than students in the *Committed Realists* profile. This is in line with findings from Winstone et al. (2021), who found that students high in conscientiousness reported being rather motivated to use feedback, which in their study resulted in higher self-reported actual use. Winstone et al. (2021) hypothesised that it may be the performance-oriented dimension of conscientiousness that promotes both the belief in the usefulness of feedback and the sense of self-efficacy

and motivation to use it effectively. Thus, in our study individuals with high levels of conscientiousness were more likely to belong to the most receptive profile, the *Committed Realists*. Additionally, the association of high levels of openness with the *Committed Realists* profile aligns with the notion that intellectual curiosity is linked to superior academic performance (Komarraju et al., 2011; Meyer et al., 2023), which in turn is associated to feedback receptivity (Bahr et al., 2024; Lipnevich & Lopera-Oquendo, 2022). Conversely, extraversion was associated with the *Empty Promisers* profile and has been associated with an increased need for social interaction, such as engaging in conversations with peers during class time (e.g. De Raad & Schouwenburg, 1996; Meyer et al., 2024; Poropat, 2009).

It is noteworthy that GPA was not associated with profile membership, even though feedback utilisation is often considered a powerful tool for enhancing academic achievement. This finding appears to contrast with previous studies using a variable-centred approach, which have shown correlations between grades, including GPA, and certain dimensions of feedback receptivity, such as students' general receptivity, their behavioral and cognitive engagement with feedback, and their experiential attitudes (e.g. Bahr et al., 2024; Lipnevich & Lopera-Oquendo, 2022). However, in our person-centred approach, the lack of correlation may be explained by the fact that these dimensions were not consistently high or low across profiles. For instance, students in the *Committed Realists* profile scored high on general receptivity but lower on cognitive engagement and experiential attitudes, which may explain the lack of a straightforward GPA correlation. In addition, this discrepancy suggests that the complex interactions captured by profile membership might require consideration of additional factors, especially in a sample as heterogeneous as our study. For instance, important socio-cultural factors, such as the quality of the relationship with the feedback provider, were not examined in our study. Research indicates that these factors can significantly influence students' decisions to utilise or disregard feedback (e.g. Luo, 2023; Sargeant et al., 2010) and thus may also influence GPA. This underscores the value of integrating psychological approaches with socio-cultural dimensions in future research to capture the full landscape of feedback receptivity. Future studies could explore factors such as the quality of the relationship with the feedback provider and the context of feedback delivery, and how these mediate or moderate the relationship between profile membership and academic outcomes.

In addressing our final research question, we discovered that mere behavioral engagement with feedback does not seem to be enough for revision performance. This is evident from our finding that students in the *Empty Promisers* profile, characterised by low levels of behavioral engagement, did not significantly differ in revision performance from those associated with the *Committed Realists* profile, who exhibited high levels of behavioral engagement. This finding highlights the added value of adopting a person-centred approach. In contrast to previous findings from a variable-centred approach, which implied that behavioral engagement alone could lead to performance enhancements (see Lipnevich & Lopera-Oquendo, 2022), our results suggest that additional factors may influence the translation of behavioral engagement into effective revision outcomes (see Lipnevich & Lopera-Oquendo, 2022). To extend our findings, process data could offer additional insights into how behavioural engagement impacts revision performance. For instance, a recent study by Schiller et al. (2024) found that behavioral engagement, measured by revision time and edit distance, mediated the positive effect

of feedback on revision performance. Therefore, future studies could complement self-reported behavioral engagement with log-data to gain a more comprehensive understanding of the effectiveness of feedback.

The absence of performance differentiation between the *Empty Promisers* and *Committed Realists* profiles shows that behavioral engagement operates in concert with other factors in shaping feedback responsiveness and performance outcomes. Simply engaging with feedback appears insufficient if not complemented by other facilitating elements captured in our profile clusters. For instance, while students in the *Committed Realists* profile demonstrated high behavioral engagement, they also exhibited high cognitive engagement and had positive experiential and instrumental attitudes towards feedback – an advantageous configuration of characteristics.

In contrast, the *Empty* Promisers profile likely experienced deterrents from their low cognitive engagement, low general receptivity, and their low attitudes towards the process of receiving feedback. These factors could dampen the impact of their behaviorally engaged tendencies.This observation supports previous research indicating how students cognitive and affective characteristics can pose motivational hurdles to effective feedback utilisation (e.g. Brown & Glover, 2006).

However, the lack of a statistically significant difference in revision performance between the *Empty Promisers* and *Committed Realists* profiles may also stem from unmeasured factors. It is possible that, for these two groups, believing the task was worthwhile (i.e. high task value) overshadowed differences in their behavioral engagement with feedback. Although the *Empty Promisers* reported lower engagement with feedback, they may have valued the writing task enough to compensate for their typically lower behavioral engagement. In other words, if a student perceives a task as highly valuable, they may perform well regardless of their usual engagement with feedback. Conversely, a student who assigns little value to the task may disengage from feedback, even if they are generally behaviorally active. Future research incorporating direct measures of task value would help clarify whether one group perceived the task as more (or less) meaningful than the other, thereby influencing both feedback receptivity and overall performance. Additionally, further studies could examine whether these receptivity profiles extend beyond feedback to other educational interventions, clarifying whether they reflect a general pattern of disengagement or one specific to feedback contexts.

Interventions designed to help students navigate the feedback process should emphasise feedback as a tool that enhances their agency and capacity to use it effectively (Jensen et al., 2021). Based on our findings, we propose targeted feedback interventions tailored to different receptivity profiles. For instance, *Indifferent Nonresponders* may require explicit scaffolds to foster a more positive attitude towards feedback – potentially through process-oriented feedback, which has been shown to enhance perceived usefulness (Harks et al., 2014). *Empty Promisers*, on the other hand, might benefit from structured, step-by-step revision guidance to help translate their initial willingness into concrete action (Sadler, 2010). Meanwhile, *Committed Realists* could gain the most from agentic feedback that challenges and extends their abilities rather than offering basic encouragement (Griffiths et al., 2023). By adapting feedback systems to students' receptivity profiles, instructional support can become more precise and effective, particularly in digital learning environments.

Limitations

Some limitations must be considered when interpreting and generalising the results of this study. First, our findings are specific to the quality and type of feedback provided in our study. The feedback messages offered useful information, yet they showed limited effects on students' revision performance. This means that our results cannot be extended to situations involving lower-quality or incorrect feedback – an increasingly important factor with the rise of AI-generated feedback. Similarly, our findings may not apply to high-quality, personalised feedback typically provided by teachers. Future research should explore the effects of varying feedback quality, with particular attention to whether students in various receptivity profiles respond differently to lower or higher quality feedback.

Second, although we conducted our analysis in a comparatively large sample, the profiles identified in this study need to be validated in other samples and student cohorts. Replicating these findings in diverse contexts – such as different countries, or across various educational stages – would provide valuable insights into the generalisability of the identified profiles. This replication would help ascertain whether similar patterns of student engagement with feedback emerge across different educational stages and contexts. In addition, we acknowledge that the three-profile solution demonstrated a lower model fit compared to more complex profile solutions, indicating that the profiles did not fully capture all the variance in the data. While we acknowledge this limitation in our ability to perfectly describe the students, we opted for the three-profile model to inform educational practice. Introducing additional profiles would have resulted in very small group sizes (less than 1% of the data), which would have been impractical for teachers to use in the classroom. However, studies with different objectives may benefit from exploring other class sizes for a more nuanced analysis.

Third, we used only a general measure of receptivity to feedback alongside a single, context-specific task and feedback instance. While our findings offer insight into students' overall tendencies to accept feedback, receptivity may also be situational and context-dependent (Lipnevich & Lopera-Oquendo, 2022). Future research should explore how students in the identified profiles respond to different assignments – particularly those they perceive as more or less valuable – and examine the stability of these profiles over time. In addition, to develop a more nuanced understanding of how students' trait-like RIF manifests in specific tasks, future studies should incorporate state-like perceptions of feedback usefulness. For example, it would be valuable to examine whether students' perceptions of feedback usefulness vary by profile membership. One might expect that students in more receptive profiles perceive feedback as more useful due to their positive instrumental attitudes towards it. Ultimately, further research is needed to better understand how stable and situational factors interact to shape students' receptivity to feedback, thereby fostering their agency and ability to use feedback effectively for learning (Jensen et al., 2021).

Conclusion and implications

Although feedback research is a highly prolific field (Winstone & Nash, 2023), we are still far from having a comprehensive understanding of what constitutes the most effective feedback. Nonetheless, our study has attempted to shed light into the black box (Lui & Andrade, 2022) of feedback processing, as we have identified groups of students who differ in their feedback acceptance and thus ultimately in their feedback processing. Hence, the identification of RIF profiles can help to understand why some students benefit more from feedback than others (Lipnevich & Smith, 2022; Lipnevich et al., 2016; Murano et al., 2021). The efforts undertaken in this study can enable researchers and practitioners to develop feedback interventions that are specifically tailored to students' individual RIF profiles.

Note

1. The 'other' gender category in our data was excluded from the profile membership analysis due to its limited sample size, which raised concerns about statistical reliability and interpretability. While it is ethically and inclusively preferable to represent all participants' identities, the small sample size for the 'other' category risked introducing bias into the model through unstable parameter estimates and inflated standard errors. Any estimated effects for the 'other' category would likely reflect sampling variation rather than true population-level differences, compromising the validity of the analysis. This issue is further compounded by the heterogeneity of identities grouped within the 'other' category, which includes a diverse range of genders. Thus, the decision to exclude this category was made to ensure the robustness and validity of the findings, despite the desire to include any participant group.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used DeepL and OpenAI's GPT-4 in order to edit sentences. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Notes on contributors

J. Luca Bahr is a doctoral candidate interested in instructional feedback, adaptive learning, individual differences, formative assessment, and artificial intelligence in education.

Lars Höft is a postdoctoral researcher interested in fostering knowledge acquisition and motivation using artificial intelligence in education.

Anastasiya Lipnevich is a full professor interested in instructional feedback, formative assessment, alternative ways of cognitive and non-cognitive assessment, and the role of psychosocial characteristics in individuals' academic and life achievement.

Jennifer Meyer is a postdoctoral researcher interested in using artificial intelligence in language learning, determinants of school performance and academic motivation.

Thorben Jansen is a postdoctoral researcher interested in adaptive learning, artificial intelligence in education, teachers' diagnostic competence and students' academic motivation.

ORCID

J. Luca Bahr http://orcid.org/0000-0002-4032-0565
Lars Höft http://orcid.org/0000-0002-9040-8995
Anastasiya Lipnevich http://orcid.org/0000-0003-0190-8689
Jennifer Meyer http://orcid.org/0000-0002-5714-3198
Thorben Jansen http://orcid.org/0000-0001-9714-6505

References

Asparouhov, T., & Muthén, B. (2005). Multivariate statistical modeling with survey data. *The 2005 FCSM Research Conference* (pp. 14–16).

Bahr, J. L., Höft, L., Meyer, J., & Jansen, T. (2024). Receptivity to instructional computer-based feedback (RIF). *European Journal of Psychological Assessment*. Advance online publication. https://doi.org/10.1027/1015-5759/a000841

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling: A Multidisciplinary Journal*, *23*(1), 20–31. https://doi.org/10.1080/10705511.2014.955104

Brockner, J., Derr, W. R., & Laing, W. N. (1987). Self-esteem and reactions to negative feedback: Toward greater generalizability. *Journal of Research in Personality*, *21*(3), 318–333. https://doi.org/10.1016/0092-6566(87)90014-6

Brown, E., & Glover, C. (2006). Evaluating written feedback. In *Innovative assessment in higher education*. Edited By Bryan,C., and Clegg, K, (pp. 81–91). Routledge.

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research*, *21*(2), 230–258. https://doi.org/10.1177/0049124192021002005

Clark, S. L., & Muthén, B. O. (2009). *Relating latent class analysis results to variables not included in the analysis* [unpublished manuscript].

De Raad, B., & Schouwenburg, H. C. (1996). Personality in learning and education: A review. *European Journal of Personality*, *10*(5), 303–336. https://doi.org/10.1002/(SICI)1099-0984(199612)10:5<303::AID-PER262>3.0.CO;2-2

Fyfe, E. R., DeCaro, M. S., & Rittle-Johnson, B. (2015). When feedback is cognitively-demanding: The importance of working memory capacity. *Instructional Science*, *43*(1), 73–91. https://doi.org/10.1007/s11251-014-9323-8

Griffiths, C. M., Murdock-Perriera, L., & Eberhardt, J. L. (2023). "Can you tell me more about this?": Agentic written feedback, teacher expectations, and student learning. *Contemporary Educational Psychology*, *73*, 102145. https://doi.org/10.1016/j.cedpsych.2022.102145

Harks, B., Rakoczy, K., Hattie, J., Besser, M., & Klieme, E. (2014). The effects of feedback on achievement, interest and self-evaluation: The role of feedback's perceived usefulness. *Educational Psychology*, *34*(3), 269–290. https://doi.org/10.1080/01443410.2013.785384

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, *77*(1), 81–112. https://doi.org/10.3102/003465430298487

Heller, K., & Perleth, C. (2000). *Kognitiver Fähigkeitstest für 4. bis 12. Klassen, Revision: KFT 4-12 +R; Manual*. Beltz.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jansen, T., Höft, L., Bahr, J. L., Kuklick, L., & Meyer, J. (2025). Constructive feedback can function as a reward: Students' emotional profiles in reaction to feedback perception mediate associations with task interest. *Learning & Instruction*, *95*, 102030. https://doi.org/10.1016/j.learninstruc.2024.102030

Jensen, L. X., Bearman, M., & Boud, D. (2021). Understanding feedback in online learning - a critical review and metaphor analysis. *Computers & Education*, *173*, 104271. https://doi.org/10.1016/j.compedu.2021.104271

Keller, S. D., Fleckenstein, J., Krüger, M., Köller, O., & Rupp, A. A. (2020). English writing skills of students in upper secondary education: Results from an empirical study in Switzerland and Germany. *Journal of Second Language Writing*, *48*, 100700. https://doi.org/10.1016/j.jslw.2019.100700

Keller, S. D., Lohmann, J., Trüb, R., Fleckenstein, J., Meyer, J., Jansen, T., & Möller, J. (2024). Language quality, content, structure: What analytic ratings tell us about EFL writing skills at upper secondary school level in Germany and Switzerland. *Journal of Second Language Writing*, *65*, 101129. https://doi.org/10.1016/j.jslw.2024.101129

Kluger, A. N., & DeNisi, A. (1996). The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin*, *119*(2), 254–284. https://doi.org/10.1037/0033-2909.119.2.254

KMK, (2020). *Bildungsstandards im Fach Biologie für die Allgemeine Hochschulreife*.

Komarraju, M., Karau, S. J., Schmeck, R. R., & Avdic, A. (2011). The Big Five personality traits, learning styles, and academic achievement. *Personality & Individual Differences*, *51*(4), 472–477. https://doi.org/10.1016/j.paid.2011.04.019

Kovaleva, A., Beierlein, C., Kemper, C. J., & Rammstedt, B. (2013). Psychometric properties of the BFI-K: A cross-validation study. *The International Journal of Educational and Psychological Assessment*, *13*(1), 34–50. https://psycnet.apa.org/record/2013-27695-003

Lipnevich, A. A., Berg, D., & Smith, J. K. (2016). *Toward a model of student response to feedback*. Routledge.

Lipnevich, A. A., Gjicali, K., Asil, M., & Smith, J. K. (2021). Development of a measure of receptivity to instructional feedback and examination of its links to personality. *Personality & Individual Differences*, *169*, 110086. https://doi.org/10.1016/j.paid.2020.110086

Lipnevich, A. A., & Lopera-Oquendo, C. (2022). Receptivity to instructional feedback: a validation study in the secondary school context in Singapore. *European Journal of Psychological Assessment*, *39*(3), 165–175. https://doi.org/10.1027/1015-5759/a000733

Lipnevich, A. A., & Smith, J. K. (2022). Student - Feedback interaction model: Revised. *Studies in Educational Evaluation*, *75*, 101208. https://doi.org/10.1016/j.stueduc.2022.101208

Lui, A. M., & Andrade, H. L. (2022). The next black box of formative assessment: a model of the internal mechanisms of feedback processing. *Frontiers in Education*, *7*. https://doi.org/10.3389/feduc.2022.751548

Luo, D., Thompson, L. A., & Detterman, D. K. (2006). The criterion validity of tasks of basic cognitive processes. *Intelligence*, *34*(1), 79–120. https://doi.org/10.1016/j.intell.2004.12.003

Luo, N. (2023). Teacher behaviour and student engagement with L2 writing feedback: A case study. *International Review of Applied Linguistics in Language Teaching*. https://doi.org/10.1515/iral-2023-0132

Mammadov, S. (2022). Big five personality traits and academic performance: A meta-analysis. *Journal of Personality*, *90*(2), 222–255. https://doi.org/10.1111/jopy.12663

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(2), 191–225. https://doi.org/10.1080/10705510902751010

Meyer, J., Jansen, T., Hübner, N., & Lüdtke, O. (2023). Disentangling the association between the big five personality traits and student achievement: Meta-analytic evidence on the role of domain specificity and achievement measures. *Educational Psychology Review*, *35*(1), 12. https://doi.org/10.1007/s10648-023-09736-2

Meyer, J., Lüdtke, O., Schmidt, F. T. C., Fleckenstein, J., Trautwein, U., & Köller, O. (2024). Conscientiousness and cognitive ability as predictors of academic achievement: evidence of synergistic effects from integrative data analysis. *European Journal of Personality*, *38*(1), 36–52. https://doi.org/10.1177/08902070221127065

Murano, D., Lipnevich, A. A., Walton, K. E., Burrus, J., Way, J. D., & Anguiano-Carrasco, C. (2021). Measuring social and emotional skills in elementary students: Development of self-report Likert, situational judgment test, and forced choice items. *Personality & Individual Differences*, *169*, 110012. https://doi.org/10.1016/j.paid.2020.110012

Muthén, L. K., & Muthén, B. O. (1998). *Mplus user's guide* (8th ed.). Muthén & Muthén.

Narciss, S., Sosnovsky, S., Schnaubert, L., Andrès, E., Eichelmann, A., Goguadze, G., & Melis, E. (2014). Exploring feedback and student characteristics relevant for personalizing feedback strategies. *Computers & Education*, *71*, 56–76. https://doi.org/10.1016/j.compedu.2013.09.011

Osborne, J., & Pimentel, D. (2022). Science, misinformation, and the role of education. *Science (New York, NY)*, *378*(6617), 246–248. https://doi.org/10.1126/science.abq8093

Panadero, E. (2023). Toward a paradigm shift in feedback research: Five further steps influenced by self-regulated learning theory. *Educational Psychologist*, *58*(3), 193–204. https://doi.org/10.1080/00461520.2023.2223642

Panadero, E., & Lipnevich, A. A. (2022). A review of feedback models and typologies: Towards an integrative model of feedback elements. *Educational Research Review*, *35*, 100416. https://doi.org/10.1016/j.edurev.2021.100416

Parchmann, I., & Kuhn, J. (2018). Lernen im Kontext. In D. Krüger, I. Parchmann, & H. Schecker (Eds.), *Theorien in der naturwissenschaftsdidaktischen Forschung* (pp. 193–207). Springer. https://doi.org/10.1007/978-3-662-56320-5_12

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338. https://doi.org/10.1037/a0014996

Rammstedt, B., & John, O. P. (2005). Kurzversion des Big Five Inventory (BFI-K). *Diagnostica*, *51*(4), 195–206. https://doi.org/10.1026/0012-1924.51.4.195

Roth, B., Becker, N., Romeyke, S., Schäfer, S., Domnick, F., & Spinath, F. M. (2015). Intelligence and school grades: A meta-analysis. *Intelligence*, *53*, 118–137. https://doi.org/10.1016/j.intell.2015.09.002

Sadler, D. R. (2010). Beyond feedback: Developing student capability in complex appraisal. *Assessment & Evaluation in Higher Education*, *35*(5), 535–550. https://doi.org/10.1080/02602930903541015

Sargeant, J., Armson, H., Chesluk, B., Dornan, T., Eva, K., Holmboe, E., Lockyer, J., Loney, E., Mann, K., & van der Vleuten, C. (2010). The processes and dimensions of informed self-assessment: A conceptual model. *Academic Medicine*, *85*(7), 1212. https://doi.org/10.1097/ACM.0b013e3181d85a4e

Schaller, N.-J., Horbach, A., Höft, L. I., Ding, Y., Bahr, J. L., Meyer, J., & Jansen, T. (2024). DARIUS: A comprehensive learner corpus for argument mining in german-language essays. In N. Calzolari, M.-Y. Kan, V. Hoste, A. Lenci, S. Sakti, & N. Xue (Eds.). *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)* (pp. 4356–4367). ELRA and ICCL. https://aclanthology.org/2024.lrec-main.389

Schiller, R., Fleckenstein, J., Mertens, U., Horbach, A., & Meyer, J. (2024). Understanding the effectiveness of automated feedback: Using process data to uncover the role of behavioral engagement. *Computers & Education*, *223*, 105163. https://doi.org/10.1016/j.compedu.2024.105163

Servaas, M. N., Riese, H., Renken, R. J., Marsman, J.-B. C., Lambregs, J., Ormel, J., Aleman, A., & Zang, Y.-F. (2013). The effect of criticism on functional brain connectivity and associations with neuroticism. *PLOS ONE*, *8*(7), e69606. https://doi.org/10.1371/journal.pone.0069606

Stanat, P., Schipolowski, S., Schneider, R., Weirich, S., Henschel, S., & Sachse, K. A. (2023). IQB-Bildungstrend 2022. Sprachliche Kompetenzen am Ende der 9. *Jahrgangsstufe im dritten Ländervergleich*. Waxmann.

Steegh, A., Höffler, T., Höft, L., & Parchmann, I. (2021). Exploring science competition participants' expectancy-value perceptions and identification: A latent profile analysis. *Learning & Instruction*, *74*, 101455. https://doi.org/10.1016/j.learninstruc.2021.101455

Tein, J.-Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, *20*(4), 640–657. https://doi.org/10.1080/10705511.2013.824781

Timmers, C. F., Walraven, A., & Veldkamp, B. P. (2015). The effect of regulation feedback in a computer-based formative assessment on information problem solving. *Computers & Education*, *87*, 1–9. https://doi.org/10.1016/j.compedu.2015.03.012

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*(4), 450–469. https://doi.org/10.1093/pan/mpq025

Wang, M., Burlacu, G., Truxillo, D., James, K., & Yao, X. (2014). Age differences in feedback reactions: The roles of employee feedback orientation on social awareness and utility. *The Journal*, *100*(4), 1296–1308. https://doi.org/10.1037/a0038334

Weiss, G., Schlüter, K., Schäbitz, F., Meyer, M., Kuckuck, M., & Budke, A. (2015). *Fachlich argumentieren lernen*. Didaktische Forschungen zur Argumentation in den Unterrichtsfächern. pedocs. http://nbn-resolving.de/urn:nbn:de:0111-pedocs-140219

Winstone, N. E., Balloo, K., & Carless, D. (2022). Discipline-specific feedback literacies: A framework for curriculum design. *Higher Education*, *83*(1), 57–77. https://doi.org/10.1007/s10734-020-00632-0

Winstone, N. E., Hepper, E. G., & Nash, R. A. (2021). Individual differences in self-reported use of assessment feedback: The mediating role of feedback beliefs. *Educational Psychology*, *41*(7), 844–862. https://doi.org/10.1080/01443410.2019.1693510

Winstone, N. E., & Nash, R. A. (2023). Toward a cohesive psychological science of effective feedback. *Educational Psychologist* 58(3). 111–129. https://doi.org/10.1080/00461520.2023.2224444

Wisniewski, B., Zierer, K., & Hattie, J. (2020). The power of feedback revisited: A meta-analysis of educational feedback research. *Frontiers in Psychology*, *10*, 3087. https://doi.org/10.3389/fpsyg.2019.03087