
**Why Some Benefit More Than Others:
Individual Differences in Receptivity to Feedback**

DISSERTATION

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Summary

Feedback plays a pivotal role in modern instructional practices, serving as a key tool to enhance learning across various educational settings (Panadero & Lipnevich, 2022). Advances in educational technology have further facilitated the delivery of personalized feedback, promoting greater equity in learning opportunities (Mertens et al., 2022). This is especially critical in light of teacher shortages (e.g., Jensen, 2021) and the increasing prevalence of online education, where automated feedback provides scalable solutions. While the potential of feedback to improve learning outcomes is well-established (e.g., Camacho et al., 2021; Graham et al., 2015, 2023, 2024), its effectiveness remains inconsistent, varying across individual learners (Wisniewski et al., 2020). Despite decades of research on how feedback influences learning outcomes (Bangert-Drowns et al., 1991; Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Kulhavy, 1977; for a historical overview see Lipnevich & Panadero, 2021), the reasons why some students benefit more from feedback than others remain unclear (Winstone & Nash, 2023).

To address these individual differences, recent feedback research has shifted its focus from feedback content to the crucial role of student characteristics—such as receptivity to feedback, perceptions of feedback, cognitive ability, personality traits, prior achievement, age, and gender—in shaping the impact of feedback on learning outcomes (Panadero & Lipnevich, 2022). A key principle in this paradigm is that feedback only influences learning if students actively engage with it (Henderson et al., 2019). This underscores a significant issue: Many students, despite receiving feedback, fail to improve due to a lack of engagement (Mensink & King, 2020; Winstone et al., 2021; Wu & Schunn, 2020).

The variability in feedback effectiveness stems from the fact that feedback is not a one-size-fits-all solution (Fleckenstein et al., 2023). For students to engage meaningfully with feedback, they need the knowledge, skills, attitudes, and dispositions required to interpret and apply it effectively—collectively referred to as *feedback literacy* (Carless & Boud, 2018; Dawson et al., 2023; Molloy et al., 2020; Nieminen & Carless, 2022). Crucially, *feedback literacy* depends on students' willingness to accept feedback. This willingness is encompassed by the concept of receptivity to instructional feedback (RIF), a multidimensional construct introduced by Lipnevich et al. (2021), which includes students' behavioral and cognitive engagement with feedback, along with their instrumental and experiential attitudes toward it.

RIF may serve as a crucial precursor to the development of *feedback literacy* and the effectiveness of feedback. However, given the novelty of this construct, its relation to factors influencing feedback reception and use remains underexplored. Additionally, evidence linking RIF to performance and motivation in real-world learning environments is limited. This dissertation seeks to address these research gaps by investigating the overarching question: Why do some students benefit more from feedback than others? Specifically, the present work investigates two central research questions:

- 1) How does students' receptivity to instructional feedback relate to other individual characteristics important for the reception and agentic use of feedback?
- 2) How does students' receptivity to instructional feedback relate to (a) performance and (b) interest?

In three empirical studies, these research questions were examined within a digital learning environment that used automated computer-based feedback to enhance argumentative writing skills. Study 1 established the foundation for the subsequent studies by validating an adapted and translated version of the RIF scale for use in computer-based assessment settings in German-speaking regions. Given that the psychometric properties of adapted instruments may differ from their original versions (Gudmundsson, 2009), thorough validation is essential (Beaton et al., 2000; Hofverberg & Winberg, 2020; Leitgöb et al., 2022). Using data from German-speaking university students ($N = 464$; $M_{age} = 24.3$, $SD = 4.4$) and secondary school students ($N = 1,207$; $M_{age} = 16.0$, $SD = 1.4$), the bifactor-CFA model demonstrated a good fit, identifying a general receptivity factor alongside four specific factors: experiential attitudes, instrumental attitudes, cognitive engagement, and behavioral engagement. Scalar measurement invariance allowed for comparisons across gender and educational levels. Convergent validity was supported by positive associations with GPA, while distinct relations between receptivity dimensions and personality traits confirmed discriminant validity. Study 1 addressed the first research question by examining how students' receptivity to instructional feedback relates to individual characteristics essential for feedback reception and agentic use while also confirming the reliability of the adapted and translated RIF scale.

Study 2 primarily addressed the second research question by investigating how the general and the four specific dimensions of RIF influence revision performance and task interest, with a particular focus on the mediating role of perceived feedback usefulness. This study involved 1,507 German-speaking secondary school students ($M_{age} = 16.4$, $SD = 1.4$) who wrote an essay in a classroom setting, received automated feedback on their performance, and revised their

work. Structural equation modeling showed that trait-like RIF factors, specifically behavioral engagement and instrumental attitudes, were critical for improving revision performance. Additionally, state-like perceptions of feedback usefulness mediated the relationship between general receptivity and increased task interest. Beyond demonstrating the links between RIF dimensions and meaningful educational outcomes, this study also contributed to the first research question by highlighting the interplay between trait-like and state-like individual differences in shaping feedback effectiveness, thereby enriching the ongoing discussion on *feedback literacy*.

Study 3 primarily addressed the first research question and involved a large sample of secondary school students ($N = 1,800$; $M_{age} = 16.37$, $SD = 1.47$) who wrote an essay in a classroom setting, received automated feedback on their performance, and revised their work accordingly. Its goal was to provide a comprehensive representation of RIF profiles by (1) identifying and characterizing distinct profiles, (2) examining differences in profile membership based on cognitive ability, personality traits, prior achievement, age, and gender, and (3) exploring the links between RIF profiles and revisions on a writing task. Using latent profile analysis, three distinct profiles emerged, characterized by varying levels of behavioral and cognitive engagement with feedback, experiential and instrumental attitudes, and general receptivity: *Indifferent Nonresponders*, *Empty Promisers*, and *Committed Realists*. The least successful profile, *Indifferent Nonresponders*, was associated with lower cognitive ability, lower agreeableness, and higher neuroticism. Regarding RIF profiles and revision performance, the results showed no performance differences between *Empty Promisers* (low behavioral engagement) and *Committed Realists* (high behavioral engagement), suggesting that behavioral engagement alone is insufficient; rather, it seems to interact with other RIF factors to shape feedback responsiveness and performance outcomes. This finding contributes to the second research question, as Studies 1 and 2 suggested that behavioral engagement could independently drive performance improvements, whereas Study 3 emphasized the need to consider multiple interacting factors.

In conclusion, this dissertation embraces the shift in feedback research toward focusing on individual differences rather than feedback content (Panadero & Lipnevich, 2022). By validating the RIF construct, it provides a framework for understanding the variability in feedback effectiveness and emphasizes that the impact of feedback depends on the student receiving it. Identifying RIF as a critical factor highlights its potential to foster *feedback literacy*, empowering students to engage with and use feedback meaningfully to enhance

learning, and to inform strategies for scalable, technology-enhanced feedback solutions in modern education.

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Chapter 1 – General Introduction and Theoretical Background

1.1 Introduction

Feedback is key in contemporary teaching practices, as it plays a crucial role in supporting learning across various educational settings (Panadero & Lipnevich, 2022). The increasing integration of technology in education offers the potential to deliver adaptive feedback tailored to students' individual needs and preferences, thereby promoting greater equity in educational opportunities. This potential is particularly significant amid teacher shortages (e.g., Jensen, 2021) and the growing adoption of online education formats, where automated feedback provides scalable solutions. While the potential of feedback to improve learning outcomes is well documented (Camacho et al., 2021; Graham et al., 2015, 2023, 2024), the effectiveness of feedback remains inconsistent, with notable variability across individual learners (Wisniewski et al., 2020). Despite extensive research, a comprehensive understanding of why some students benefit more from feedback than others is lacking (Winstone & Nash, 2023).

To explain why feedback effectiveness varies among students, contemporary feedback research emphasizes the crucial role of student characteristics in determining whether feedback translates into learning (Panadero & Lipnevich, 2022). While much research has examined the content and delivery of feedback, many studies have indicated that its impact ultimately hinges on how students receive, interpret, and apply it (Hattie & Timperley, 2007; Kluger & DeNisi, 1996).

Recognizing this, contemporary research has called to shift the focus from feedback itself to the student's role in the feedback process (Lipnevich & Panadero, 2021). Winstone and Carless (2019) describe this shift as a transition from old to new paradigms. A central idea within this new paradigm is that feedback cannot be assumed to influence learning unless students actively engage with it (Henderson et al., 2019). This highlights a critical issue: Despite having access to feedback, many students fail to improve their performance because they do not engage with the feedback they receive (Mensink & King, 2020; Winstone et al., 2021; Wu & Schunn, 2020).

This is because feedback is not a one-size-fits-all solution (Fleckenstein et al., 2023). For students to engage with feedback effectively, it has been argued that they need *feedback literacy*, which encompasses the dispositions, knowledge, skills, and attitudes necessary to interpret and use feedback meaningfully (Carless & Boud, 2018; Dawson et al., 2023; Molloy et al., 2020; Nieminen & Carless, 2022). However, developing *feedback literacy* requires an initial willingness to accept feedback. Individual differences in students' tendencies to accept feedback are captured by the concept of receptivity to instructional feedback (RIF; Lipnevich et al., 2021). RIF encompasses students' behavioral and cognitive engagement with feedback,

as well as their instrumental and experiential attitudes toward feedback (Lipnevich et al., 2021). Students' RIF may be a crucial prerequisite for developing *feedback literacy* and, ultimately, for feedback effectiveness. However, research on this link remains scarce. Understanding students' RIF could help explain why some students benefit from feedback while others do not.

Therefore, the primary aim of this dissertation is to investigate individual differences in students' RIF and the relation of students' RIF with performance and motivational outcomes in the context of automated computer-based feedback. Furthermore, this dissertation examines how RIF relates to other well-established predictors of feedback effectiveness and to students' perceptions of feedback. To address these questions, the dissertation comprises three studies.

Study 1 laid the foundation for the subsequent studies by validating an adapted and translated version of the RIF scale for use in computer-based assessment settings in German-speaking regions. As the psychometric properties of adapted and translated instruments may differ from their original versions (Gudmundsson, 2009), thorough validation is essential (Beaton et al., 2000; Hofverberg & Winberg, 2020; Leitgöb et al., 2022). Using data from a large sample of German-speaking university and secondary school students, the study examined the factorial structure of the RIF scale, its measurement invariance across gender and educational levels, and its relations with broader personality traits and GPA.

After the RIF scale was successfully validated in Study 1, Study 2 applied the scale in an authentic writing and feedback context to examine its links with performance and motivational outcomes. RIF reflects a trait-like tendency to accept feedback (Lipnevich et al., 2021); Study 2 complemented that perspective by also considering state-like perceptions of feedback usefulness, which may vary depending on the specific feedback received (e.g., Harks et al., 2014; Rakoczy et al., 2013; 2019). Specifically, the study examined how RIF dimensions relate to performance and motivational outcomes with a particular focus on the mediating role of perceived feedback usefulness.

Finally, Study 3 adopted a person-centered approach, which considered multiple variables simultaneously, recognizing that the varying levels of RIF dimensions students exhibit may not operate independently and should therefore be analyzed jointly. For example, a student might value feedback (instrumental attitudes) and enjoy receiving it (experiential attitudes) but still struggle to implement it effectively (behavioral engagement). To complement the variable-centered approach used in Studies 1 and 2, Study 3 employed latent profile analysis to categorize students into RIF profiles. Established factors that relate to feedback effectiveness (e.g., cognitive ability, personality traits, prior achievement, age, and gender) were used to

predict profile membership, and associations between RIF profiles and revision performance on a writing task were examined.

To ensure high ecological validity, students' RIF was examined within the context of socio-scientific argumentative writing, a key focus in German K-12 education. This area integrates all aspects of the educational standards for natural sciences and equips students with the skills necessary to engage meaningfully in societal discourse (KMK, 2020; Osborne & Pimentel, 2022; Parchmann & Kuhn, 2018; Weiss et al., 2015). Despite its importance, many students struggle with argumentative writing (Keller et al., 2020, 2024; Stanat et al., 2023). By targeting this critical domain, our goal was to shed light on how feedback can be leveraged to improve students' argumentative writing abilities and overall academic success.

The remainder of this chapter establishes the theoretical background by defining feedback, outlining its functions, and discussing the crucial role of the learner in the feedback process. The chapter then introduces the central construct of this dissertation (i.e., RIF) and further examines the relation between feedback and both performance and motivational outcomes. Finally, it presents the dissertation's research questions and an overview of the three empirical studies that are subsequently presented in manuscript format in Chapters 2 to 4. Chapter 5 provides a summary of each study and concludes with an integrated discussion of the findings in relation to the leading research questions.

1.2 From Feedback Content to Feedback Literacy: The Historical Development of Feedback Definitions

Since the start of the last century, numerous researchers have developed definitions and models of feedback that serve as effective theoretical frameworks for studying feedback within diverse educational settings. Thorndike's Law of Effect and Skinner's theory of behaviorism, with its concepts of positive and negative reinforcement and punishment, can be seen as an early foundation for what is now understood as instructional feedback in the field (Thorndike, 1913, 1927; Skinner, 1968). From the behaviorist perspective, feedback was seen as corrective information that reinforced correct responses and suppressed incorrect ones through punishment. This mechanistic view emphasized the reduction of errors but offered no detailed explanation of error correction or the methods that could be used to achieve it. Decades later, research began to emphasize feedback as a learning opportunity rather than solely as a mechanism for correcting errors (Kulhavy, 1977; Sadler, 1989). Nonetheless, feedback was still defined as "any of the numerous procedures that are used to tell a learner if an instructional

response is right or wrong” (Kulhavy, 1977, p. 211). The concept of formative assessment emphasizes feedback’s capacity to enhance learning outcomes, narrow achievement gaps, and guide teaching practices (Bloom, 1971). Sadler (1989) expanded on this concept, describing feedback as “a key element in formative assessment [...] usually defined in terms of information about how successfully something has been or is being done” (p. 120). Sadler identified three essential conditions that need to be fulfilled for feedback to effectively promote learning. First, feedback must clearly articulate the goal students are expected to achieve. Second, students need to evaluate their actual performance against this goal. Third, they must take action to close the gap between their current performance and the desired outcome. While Sadler (1989) recognized the student’s role in bridging this gap, these three conditions were still emphasized primarily within the context of feedback content.

In the 1990s, feedback research began to focus on the role of feedback in learning processes, particularly in fostering cognitive engagement (e.g., Butler & Winne, 1995). Mason and Bruning’s (2001) work was the first to introduce the concept of individual differences in cognitive engagement within the context of computer-based instruction. Mason and Bruning (2001) defined feedback as “any message generated in response to a learner’s action” (p. 3). Their model provided clear guidelines for delivering improved feedback, while accounting for important variables such as students’ achievement levels, prior knowledge, and the timing of feedback. Notably, two individual student characteristics that they discussed—“attitude towards feedback” and “learner control”—were not included in their model.

Several other researchers have proposed definitions and models of feedback that have significantly contributed to the advancement of the field (e.g., Bangert-Drowns et al., 1991; Evans, 2013; Kluger & DeNisi, 1996; Kulhavy & Stock, 1989; Lipnevich et al., 2016; Narciss, 2008; Nicol & Macfarlane-Dick, 2006; Ramaprasad, 1983; Tunstall & Gipps, 1996; see Lipnevich & Panadero, 2021 for a historical overview). However, the most influential remains the model by Hattie and Timperley (2007), who defined feedback as “information provided by an agent (e.g., teacher, peer, book, parent, self, experience) regarding aspects of one’s performance or understanding” (p. 81). This definition, like many others, highlights the content of feedback as its central focus. However, evidence has shown that feedback’s effectiveness depends significantly on how it is received and applied (Hattie & Timperley, 2007; Kluger & DeNisi, 1996). This has led to a pivotal shift in feedback research toward prioritizing the learner’s perspective. Although the content of the feedback message is undeniably important, feedback is only effective when it is actively used. Consequently, contemporary research emphasizes the learner’s active role in interpreting and responding to feedback (Lipnevich et

al., 2016; Carless & Boud, 2018; Shute, 2008). It also underscores the vital importance of student engagement in the feedback process and explores the factors that shape this engagement (Boud, 2000; Winstone et al., 2017; Jonsson & Panadero, 2018). In recent years, particular attention has been given to individual student characteristics—such as receptivity, perceptions, cognitive ability, personality traits, prior achievement, age, and gender—and their interaction with feedback messages (Evans, 2013; Lipnevich et al., 2016; Lipnevich & Smith, 2022). A closely related concept emerging from this research is *feedback literacy*, which encompasses the knowledge, skills, and attitudes students require to engage effectively with feedback (Carless & Boud, 2018; Dawson et al., 2023; Molloy et al., 2020; Nieminen & Carless, 2022).

In an extensive review, Lipnevich and Panadero (2021) analyzed and synthesized 14 leading feedback models (Bangert-Drowns et al., 1991; Butler & Winne, 1995; Carless & Boud, 2018; Evans, 2013; Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Kulhavy & Stock, 1989; Lipnevich et al., 2016; Mason & Bruning, 2001; Narciss, 2008; Nicol & Macfarlane-Dick, 2006; Ramaprasad, 1983; Sadler, 1989; Tunstall & Gipps, 1996), offering a historical overview of feedback definitions and the evolving theoretical perspectives that have shaped feedback research over time. Following this review, Lipnevich and Panadero (2021) proposed a comprehensive, contemporary definition of feedback:

“Feedback is information that includes all or several components: students’ current state, information about where they are, where they are headed and how to get there, and can be presented by different agents (i.e., peer, teacher, self, task itself, computer). This information is expected to have a stronger effect on performance and learning if it encourages students to engage in active processing.” (p. 25)

Three key aspects emerge from this definition. First, feedback is fundamentally information. Lipnevich and Panadero (2021) emphasized that feedback should align with the core questions posed by Hattie and Timperley (2007): *Where am I going?* *How am I going?* and *Where to next?* Second, feedback can be provided by various agents; this aspect highlights the diverse contexts that are relevant to feedback research and practice. Third, and most importantly, the definition stresses the critical role that students’ active engagement with feedback plays in improving their learning and performance.

In summary, Lipnevich and Panadero (2021) highlighted the student’s central role in making feedback effective. Building on this review, Panadero and Lipnevich (2022) proposed the comprehensive Message, Implementation, Student, Context, and Agents (MISCA) model, which will be introduced in the next section.

1.3 The Student as the Central Driver of Feedback Effectiveness

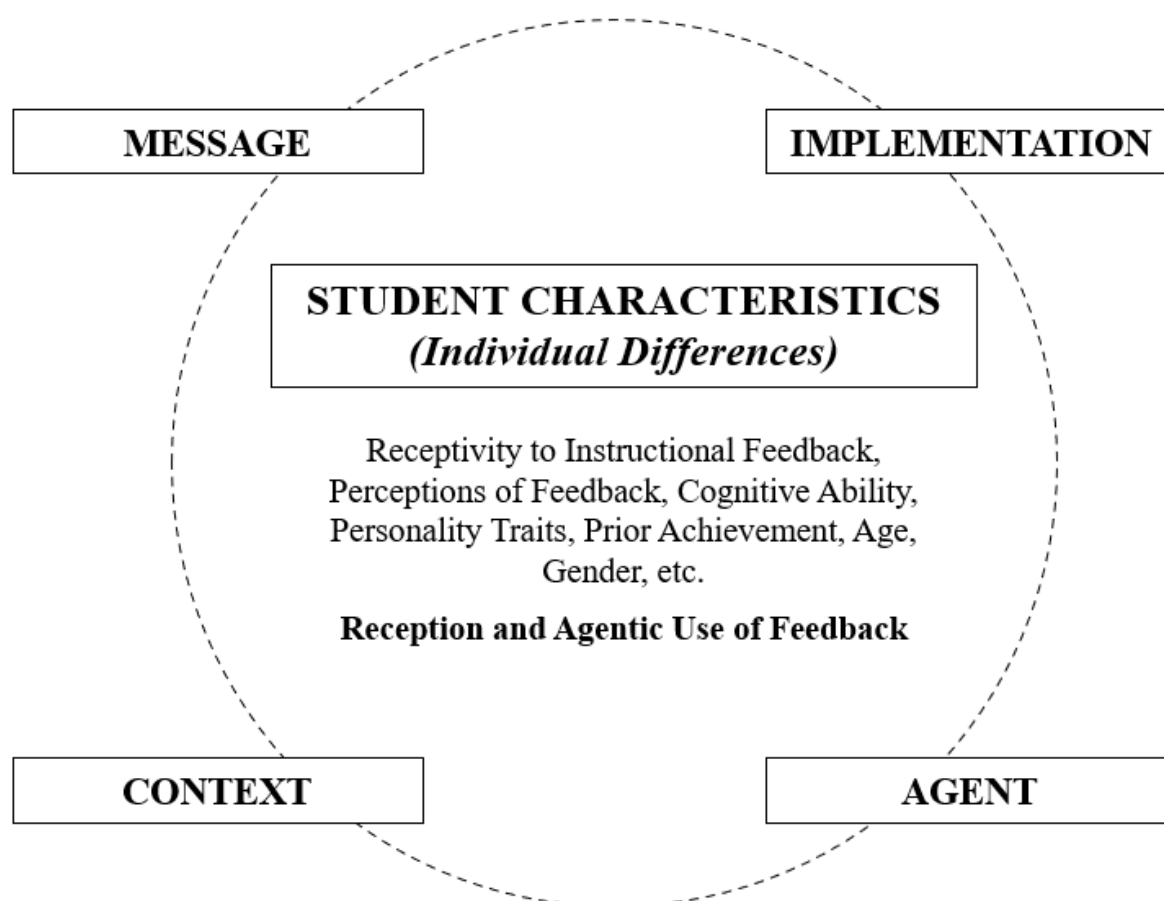
The MISCA model (Panadero & Lipnevich, 2022) represents a state-of-the-art framework by placing the student at the center of the feedback process and outlining the various factors that influence feedback effectiveness across diverse contexts. The model comprises five key elements: Message, Implementation, Student, Context, and Agents (see Figure 1.1).

The *Message* refers to the content of the feedback, which is a critical factor in determining the effectiveness of the feedback. The *Implementation* element captures the primary functions of feedback—enhancing performance and fostering motivation—and can guide how educators design feedback and how students engage with it. The *Student* is the focal point of the model, underscoring the recipient’s central role in the feedback process (see also Lipnevich et al., 2016). The *Context* emphasizes the instructional setting in which feedback is provided, highlighting the necessity of delivering feedback at a time when students can actively implement it, rather than, for instance, at the end of a course when it is likely to be disregarded. Finally, the *Agent* element emphasizes the importance of understanding the feedback source, that is, whether the feedback is provided by a teacher, a peer, the self, a task, or a computer.

Figure 1.1 provides an overview of the core components of the MISCA model, highlighting the five key factors that contribute to effective feedback practices. The model emphasizes the central role of the student in the feedback process, positioning them exactly where they belong—at its core. The following section explores the model’s central element, focusing on the crucial influence of individual differences on feedback effectiveness. Given that students’ receptivity has been identified as a particularly important factor among these differences, this construct will be explored in detail under a separate subheading.

Figure 1.1

The MISCA Model



Note. An illustration of the MISCA model, adapted from Panadero & Lipnevich, 2022, p. 13.

1.3.1 Individual Student Characteristics Important for the Reception and Agentic Use of Feedback

Panadero and Lipnevich (2022) consider the *Student* element of their model to be extremely relevant and emphasize that students deal with feedback differently depending on their individual characteristics. This thematic area is particularly important because it strongly impacts the other four areas (i.e., *Message*, *Implementation*, *Context*, and *Agent*) and focuses on how individual differences shape the way learners receive and process feedback.

One key aspect of individual differences is personality. Kluger and DeNisi (1996) found that personality traits influence how students react to and process feedback. The Big Five personality traits—conscientiousness, neuroticism, agreeableness, openness, and

extraversion—have been widely studied in relation to academic outcomes. Among these, conscientiousness is a well-established predictor of school achievement (Mammadov, 2022; Meyer et al., 2023, 2024; Poropat, 2009). Students high in conscientiousness are often motivated to use feedback effectively, as demonstrated by Winstone et al. (2021), who found that these students had a higher self-reported use of feedback. The authors hypothesized that the performance-oriented dimension of conscientiousness fosters both a belief in the usefulness of feedback and a sense of self-efficacy and motivation to implement it. In contrast, neuroticism is tied to increased sensitivity to criticism (e.g., Brockner et al., 1987; Servaas et al., 2013), which may lead students high in neuroticism to doubt their ability to use feedback effectively. This lack of confidence can impair their willingness to engage with and apply the feedback they receive, ultimately reducing the potential benefits of feedback for these students. Agreeableness has also been linked to academic achievement (e.g., Meyer et al., 2023, 2024), with agreeable students often demonstrating cooperative and constructive behavior in academic settings. Openness, characterized by intellectual curiosity, has been associated with greater academic performance (Komarraju et al., 2011; Meyer et al., 2023), as students with high openness tend to engage deeply with learning opportunities, such as feedback. Finally, extraversion has been associated with a need for social interaction, which can influence feedback engagement in both positive and negative ways. On the one hand, extraverted students may benefit from opportunities to discuss feedback with others, enhancing their engagement. On the other hand, their sociability could be a distraction, leading to off-task conversations during class (e.g., De Raad & Schouwenburg, 1996; Meyer et al., 2024; Poropat, 2009).

Beyond personality traits, cognitive ability also plays a crucial role in feedback processing. Research has consistently shown that cognitive ability is strongly associated with academic achievement (e.g., Meyer et al., 2023, 2024). Moreover, higher cognitive ability, often linked to working memory capacity, has been shown to enhance feedback processing, enabling students to better engage with and apply feedback effectively (Fyfe et al., 2015). Mason and Bruning (2001) also highlighted the importance of considering students' prior achievement levels when determining the type of feedback to deliver in computer-based instruction. Additionally, prior achievement has been linked to the agentic use of feedback and its role in enabling students to engage with feedback has been emphasized (Panadero & Lipnevich, 2022).

In addition to cognitive ability, demographic factors such as gender and age can influence students' receptivity to feedback. Evans (2013) proposed that gender is associated with differences in effective feedback uptake. For instance, 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 tended to show greater receptivity to feedback. Age-related differences also play a role in shaping students' responses to feedback (e.g., Wang et al., 2014).

Beyond inherent characteristics such as personality, cognitive ability, and demographic factors, students' subjective perceptions of feedback also influence how they engage with it. Specifically, their perception of the usefulness of the feedback plays a critical role in feedback engagement and effectiveness (Van der Kleij & Lipnevich, 2021; Panadero & Lipnevich, 2022). Students evaluate feedback by assessing its perceived usefulness, comparing it to their current understanding and performance (Bouwer & Dirkx, 2023). This evaluative process helps students determine the relevance and value of the feedback and guides their decisions on whether and how to use it to improve their performance (Boud et al., 2018; Carless & Boud, 2018; Nicol, 2021). These judgments directly influence how feedback is applied, as students are more likely to engage with feedback they perceive as useful (Ilgen et al., 1979; Jansen et al., 2025; Jonsson & Panadero, 2018; Lipnevich & Smith, 2009). However, Van der Kleij and Lipnevich (2021) conducted a scoping review of research on students' perceptions of feedback and found that few studies had explored associations between these perceptions and meaningful outcomes.

While personality traits, cognitive ability, demographic factors, and students' perceptions shape their reactions to feedback, receptivity to instructional feedback ultimately determines whether they accept and engage with it. As the MISCA model emphasizes this receptivity as a critical prerequisite for effective feedback use, the next subsection focuses on receptivity to instructional feedback in greater detail.

1.3.1.1 Receptivity to Instructional Feedback

The concept of receptivity to instructional feedback was introduced to explain why many students, despite having access to feedback, fail to improve their performance due to a lack of engagement with the feedback they receive (Mensink & King, 2020; Winstone et al., 2021; Wu & Schunn, 2020). It is founded on the idea that individuals differ in their willingness and readiness to engage with feedback (Lipnevich et al., 2016). While some students are generally eager to receive feedback, others may be less receptive (Lipnevich & Lopera-Oquendo, 2022). RIF originates from personality psychology and is defined as a trait-like disposition toward accepting and engaging with feedback (Lipnevich & Lopera-Oquendo, 2022). This multidimensional construct comprises students' behavioral ("Do I know what to do with feedback?") and cognitive engagement ("Do I understand feedback?") with feedback, and their

instrumental (“Do I think feedback is useful?”) and experiential (“Do I like feedback?”) attitudes towards feedback (Lipnevich et al., 2021). Initial evidence suggests that students with higher scores on RIF dimensions are more likely to perceive feedback as valuable, actively engage with it, internalize its message, and apply it to improve their performance (Lipnevich & Lopera-Oquendo, 2022).

To differentiate RIF from broader personality traits, Lipnevich et al. (2021) explored its associations with the Big Five dimensions of personality: conscientiousness, openness, extraversion, agreeableness, and neuroticism. Their findings revealed that the four dimensions of receptivity added incremental value beyond broader personality traits, supporting the construct’s uniqueness. Conscientiousness showed a strong positive association with all receptivity dimensions, suggesting that self-disciplined and organized students are more likely to be receptive to feedback (see also McCrae & John, 1992). Neuroticism was negatively related to cognitive engagement with feedback, indicating that self-conscious and impulsive students are less inclined to process feedback deeply (Lipnevich et al., 2021). Openness demonstrated positive associations with all receptivity dimensions, reflecting that curious students tend to be more open to feedback (Lipnevich et al., 2021). In contrast, extraversion and agreeableness had only weak links to RIF. These findings provided evidence of discriminant validity, as the RIF dimensions did not simply mirror existing personality traits.

Additionally, Lipnevich and Lopera-Oquendo (2022) demonstrated that experiential attitudes and cognitive and behavioral engagement were significant predictors of student grades, further establishing the scale’s convergent validity in forecasting key educational outcomes. Overall, the RIF instrument has proven to be a reliable measure of students’ tendency to accept feedback from educators, such as teachers or professors (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022). It is therefore plausible to suggest that students who enjoy receiving feedback (experiential attitudes), perceive it as critical to their success (instrumental attitudes), understand its content and possess strategies to interpret and apply it effectively (cognitive engagement), and act on the feedback they receive (behavioral engagement) are more likely to benefit from it compared to those who do not.

While these initial findings highlight the potential of RIF in shaping student outcomes, further research is needed to establish the extent and mechanisms of its impact. Specifically, understanding how feedback receptivity influences performance and motivation—two key educational outcomes—remains a critical avenue for investigation. The following sections explore the relationship between feedback and these key outcomes in greater depth.

1.4 Perspectives on Feedback and Performance: Bridging the Gap Between Students' Current Understanding and the Desired Learning Goal

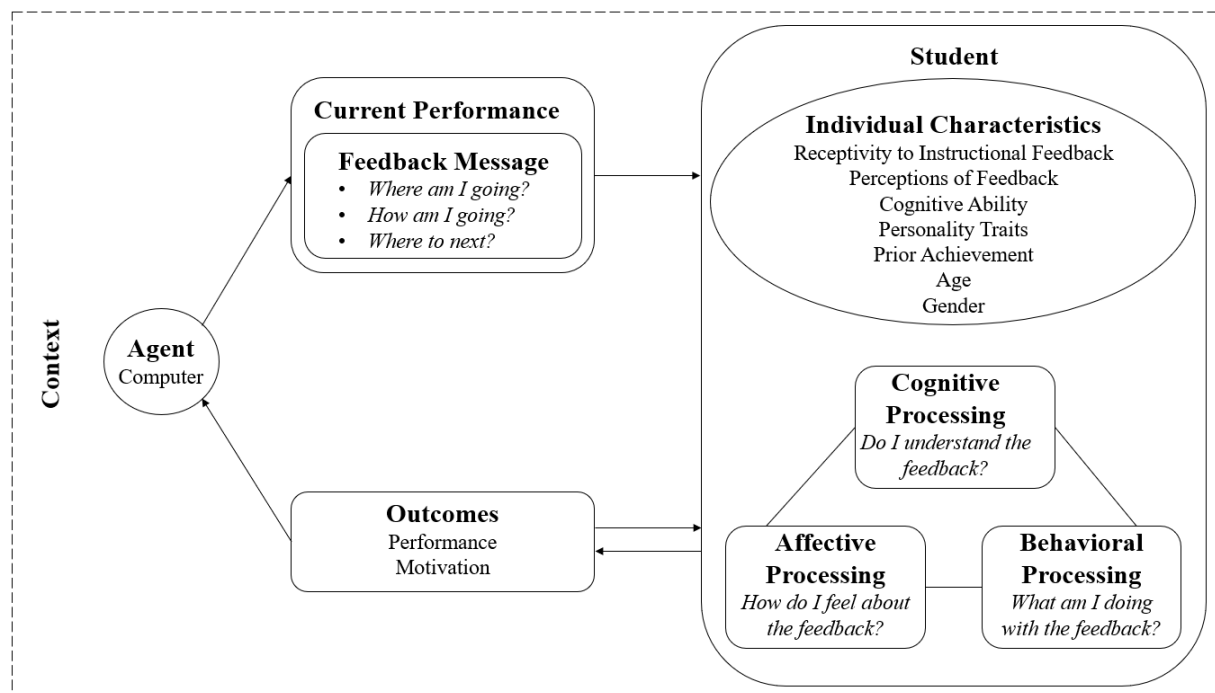
Empirical studies have consistently demonstrated that feedback significantly influences student performance. Meta-analyses focusing on writing instruction have reported medium effect sizes, with values ranging from $d = 0.30$ to $d = 0.38$ (Graham et al., 2015, 2023, 2024). Regarding the effects of computer-based feedback on writing performance, Fleckenstein et al. (2023) found a medium effect size of $g = 0.55$, ranging from -1.73 to 2.99. However, Fleckenstein et al. (2023) emphasized that automated feedback is not a one-size-fits-all solution, as its effectiveness depends on individual student characteristics. This is further illustrated by the significant variability in feedback effectiveness among students across various contexts (e.g., Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Wisniewski et al., 2020).

The first condition that needs to be met in order for feedback to improve performance is that it clearly communicates the goal that students should achieve (Sadler, 1989). The second condition requires students to compare their actual performance with this goal, and the third involves students taking actions to close the gap between their current performance and the desired goal. Sadler emphasized that all three conditions must be met for feedback to be effective. Several researchers have further developed these ideas (e.g., Bangert-Drowns et al., 1991; Butler & Winne, 1995; Kluger & DeNisi, 1996; Mason & Bruning, 2001; Narciss, 2008; Nicol & McFarlane-Dick, 2006), with Hattie and Timperley (2007) being among the most prominent. They proposed three core questions to guide feedback: *Where am I going?* *How am I going?* and *Where to next?* Consistent with Sadler's early ideas, feedback that addresses these questions helps reduce the gap between the desired goal and the student's current performance. In addressing the first question, *Where am I going?* it is crucial to clarify learning objectives and assessment criteria, thereby establishing clear expectations for performance (Reddy & Andrade, 2010). For example, in argumentative writing, students need to express a clear opinion (i.e., a major claim, Osborne et al., 2016), and this requirement should be explicitly communicated in the feedback. The second question, *How am I going?* involves evaluating student performance. Feedback is most effective when it not only provides an assessment but also explains it, helping students identify and correct their errors or misconceptions (Rich et al., 2017). For instance, feedback might indicate the absence of a major claim as an area for improvement. Finally, addressing *Where to next?* requires offering forward-looking guidance (Sadler, 2010), including specific strategies or examples to help students reach their goals.

Thus, feedback influences performance by bridging the gap between students' current performance and their desired learning goals (Bangert-Drowns et al., 1991; Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Narciss, 2008). Achieving this requires careful consideration of how students respond to and engage with feedback. Accordingly, the guiding MISCA model (Panadero & Lipnevich, 2022) emphasized in this dissertation highlights the active role of students in the feedback process as a critical factor in driving performance improvement. According to Lipnevich and Smith (2022), the feedback process itself might be best conceptualized as a loop in which the student interacts with the feedback (see Figure 1.2). This process unfolds within a specific context, beginning with the feedback itself and the agent delivering it. The next step involves the student receiving feedback and their cognitive, affective, and behavioral processing of it. The final phase focuses on the actions taken and the resulting outcomes, which can manifest in students' performance or motivation.

Figure 1.2

Process Model of the Student–Feedback Interaction



Note. The model was adapted from Lipnevich & Smith, 2022, p. 3.

1.5 Perspectives on Feedback and Motivation: Phases of Interest Development

With respect to the effects of feedback on motivation, Wisniewski et al. (2020) reported a medium effect size of $d = 0.33$, with a range from 0.23 to 0.42. Feedback has been widely recognized as a key driver of motivation (e.g., Dweck & Leggett, 1988; Eccles & Wigfield,

2020; Ryan & Deci, 2000), yet its impact can vary significantly depending on the characteristics of the learner (Hattie & Timperley, 2007; Wisniewski et al., 2020).

Most theories of learning motivation focus on individuals' thoughts, evaluations, and beliefs (see Meyer & Turner, 2002) and emphasize the mental processes that influence a learner's willingness to engage in learning activities. The integration of affect as a fundamental aspect of interest distinguishes the interest construct from other motivational constructs (Hidi & Renninger, 2006; Krapp, 1999). The four-phase model of interest suggests that interest initially emerges as an affective response, which is gradually integrated into cognitive processes as it develops and deepens (Hidi & Renninger, 2006). Interest encompasses both the psychological state individuals experience when engaging with particular content and their motivation to revisit that content over time (Hidi & Renninger, 2006; Renninger & Hidi, 2015). A new interest emerges when something captures a student's attention, a process referred to as triggering (see Renninger et al., 2019). Triggered interest may be fleeting; however, when students are encouraged to re-engage with the topic, their initial interest can develop into a well-established interest that students sustain independently (Hidi & Renninger, 2006).

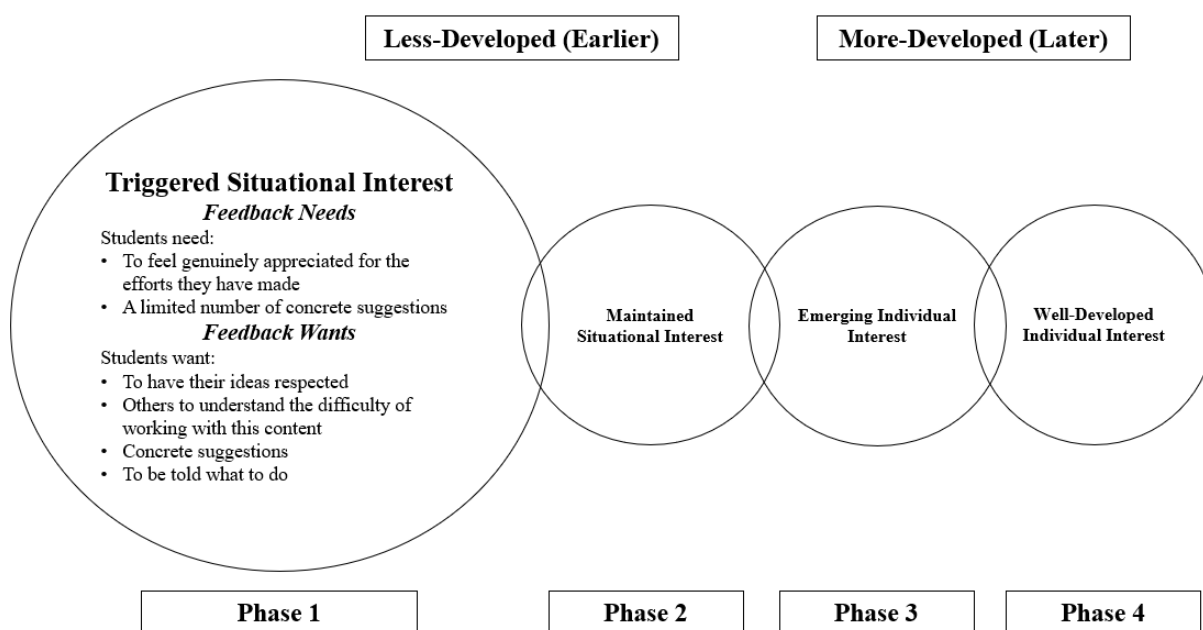
Hidi and Renninger (2006) introduced the four-phase model of interest development, which (a) outlines how interest evolves over time, (b) emphasizes the importance of researchers clearly identifying the type of interest under study, and (c) provides recommendations for educators to support the development of interest. The four phases of interest are: triggered situational interest, maintained situational interest, emerging (less-developed) individual interest, and well-developed individual interest (see Figure 1.3). The first phase, triggered situational interest, describes a psychological state of interest that arises from short-term changes in affective and cognitive processes. This type of interest can be initiated by environmental or textual elements, such as feedback. Triggered situational interest is often, though not always, externally supported. Triggered situational interest may serve as a precursor to re-engagement with specific content over time, leading to more developed phases of interest (see Renninger & Hidi, 2006).

In this phase of interest development, students have specific feedback needs and wants (see Figure 1.3). Students need feedback that offers a limited number of concrete suggestions while also recognizing their efforts, making them feel valued. Students want feedback that tells them what to do, with concrete suggestions on how to achieve this. In addition, they want to feel seen and be respected in their ideas. Feedback aligned with students' wants and needs can spark and sustain their triggered situational interest (see Renninger & Hidi, 2022). This dissertation

examines students' triggered situational interest (Phase 1 of the four-phase model of interest development), which can be facilitated by automated computer-based feedback. This focus is motivated by two key considerations: first, the importance of engaging students at their current stage of interest development, and second, the fact that there is evidence demonstrating that feedback can effectively spark this initial form of interest (Renninger & Hidi, 2006).

Figure 1.3

Feedback Wants and Feedback Needs in the Phases of Interest Development



Note. The model was adapted from Renninger & Hidi, 2022, p. 25. Phase 1 is highlighted due to the specific focus of this dissertation on the initial stage of interest development.

1.6 Research Questions of the Present Dissertation

As outlined above, the effectiveness of feedback remains inconsistent, with notable variability across individual learners (Panadero & Lipnevich, 2022; Wisniewski et al., 2020). Investigating individual differences in students' RIF seemed to be a promising approach to address the overarching question of this dissertation:

Why do some students benefit more from feedback than others?

This question was addressed with a focus on the impact of computer-based feedback in the context of socio-scientific argumentative writing. The theoretical background of this dissertation outlined several individual student characteristics (e.g., cognitive ability,

personality traits, prior achievement, age, gender, and perceptions of feedback usefulness) that have been shown to relate to the reception and agentic use of feedback (Panadero & Lipnevich, 2022). With the aim of improving the understanding of how these characteristics relate to the dimensions of students' RIF (e.g., behavioral and cognitive engagement, and instrumental and experiential attitudes), the first research question of this dissertation is:

RQ1: How does students' receptivity to instructional feedback relate to other individual characteristics important for the reception and agentic use of feedback?

This research question was investigated using both variable-centered and person-centered approaches. The variable-centered approach focused on examining associations among variables, while the person-centered approach aimed to identify subgroups of students with similar patterns across these variables. Specifically, Study 1 validated an adapted German version of the RIF scale for use with computer-based feedback, thereby creating a foundation for the following studies of this dissertation. To answer RQ1 and to examine the discriminant and convergent validity of the scale, Study 1 used a variable-centered approach to investigate the relations of the receptivity dimensions with broader personality characteristics (i.e., conscientiousness, neuroticism, agreeableness, openness, and extraversion) and prior achievement (i.e., GPA). Also using a variable-centered approach, Study 2 examined the associations of the receptivity dimensions with perceptions of feedback usefulness. Finally, Study 3 used a person-centered approach aimed at identifying (a) distinct subgroups of students based on the receptivity dimensions and (b) differences in profile membership based on cognitive ability, personality traits, prior achievement, age, and gender.

Although the findings from Lipnevich and Lopera-Oquendo (2022) suggested associations between students' RIF and performance outcomes, the theoretical background of this dissertation highlights the limited research on the relations between students' receptivity to instructional feedback and meaningful educational outcomes. Therefore, the second research question of this dissertation is:

RQ2: How does students' receptivity to instructional feedback relate to (a) performance and (b) interest?

Again, this research question was investigated using both variable-centered and person-centered approaches. Specifically, Study 2 used a variable-centered approach to examine the relations between RIF dimensions and (a) performance and (b) interest in an authentic real-world feedback context. Complementing this, Study 3 used a person-centered approach to

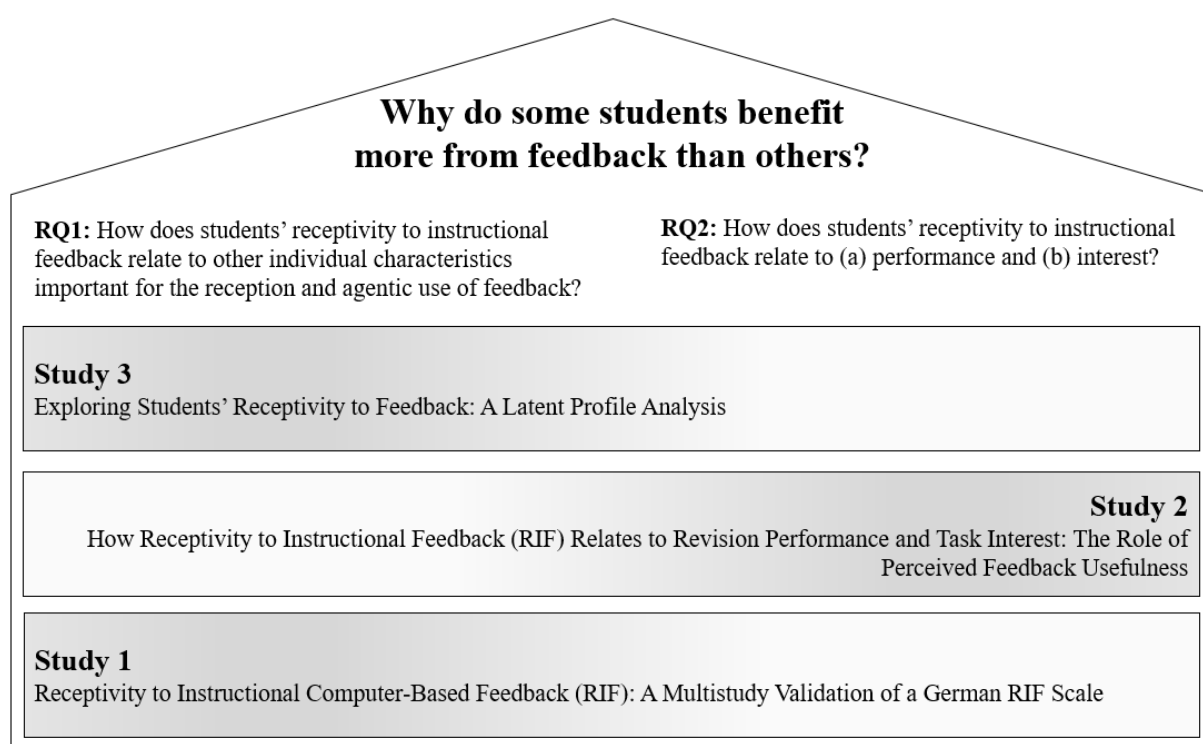
investigate associations between different RIF profiles and (a) performance on a writing task. The efforts undertaken in this dissertation can help researchers and practitioners alike to understand why some students benefit more from feedback than others.

1.7 Presentation of the Three Empirical Studies

The three studies in this dissertation are interconnected and build upon one another (see Figure 1.4). Study 1 laid the groundwork by validating an adapted German version of the RIF scale for use in computer-based feedback contexts. Building on this, Study 2 examined how dimensions of RIF relate to performance and motivational outcomes, with a particular focus on the mediating role of perceived feedback usefulness in an authentic writing and feedback context. Finally, Study 3 employed latent profile analysis to classify students into distinct RIF profiles and explored their relations with other individual characteristics critical for feedback reception and agentic use.

Figure 1.4

Overview of the Three Studies Addressing the Two Research Questions



Note. The color gradient and alignment indicate which RQ the studies primarily addressed.

1.7.1 Study 1 – Receptivity to Instructional Computer-Based Feedback (RIF): A Multistudy Validation of a German RIF Scale

Study 1 validated an adapted German version of the RIF scale for use with computer-based feedback, thereby creating a foundation for Studies 2 and 3 in this dissertation. This adaptation was necessary not only for the studies of this dissertation but also for the broader research community, as feedback is increasingly provided in computer-based assessments (Mertens et al., 2022), and the original RIF scale had only been available for human-provided feedback. According to the MISCA model, the feedback-providing agent (i.e., human or computer) may impact how feedback is received and used by students (Panadero & Lipnevich, 2022). Therefore, the role of the feedback-providing agent must be acknowledged, and the scale adapted accordingly. Additionally, scales intended for use in new contexts (and in other languages) must be tested for their psychometric properties (Beaton et al., 2000), factorial structure (e.g., Hofverberg & Winberg, 2020), and measurement invariance (Leitgöb et al., 2022). The relations of RIF with broader personality characteristics and GPA were investigated to confirm discriminant and convergent validity, respectively. The primary aim was to establish a reliable instrument for assessing feedback receptivity in German-speaking regions.

1.7.2 Study 2 – How Receptivity to Instructional Feedback (RIF) Relates to Revision Performance and Task Interest: The Role of Perceived Feedback Usefulness

Study 2 examined the relations between RIF dimensions and (a) performance and (b) interest in the context of argumentative writing. Although empirical studies have shown positive associations between RIF dimensions and academic performance (e.g., Lipnevich & Lopera-Oquendo, 2022), none have examined these trait-like tendencies together with students' state-like perceptions in real-world feedback settings. This gap is notable as it raises two possibilities: that trait-like RIF dimensions directly relate to changes in performance and interest, or that these relations are mediated by state-like perceptions of feedback usefulness. Therefore, the study investigated whether trait-like RIF dimensions relate to revision performance and task interest, and whether these relations are mediated by state-like perceptions of feedback usefulness. The consideration of state-like perceptions of feedback usefulness can not only enhance understanding of student *feedback literacy*, it can also aid to better determine the interplay of RIF dimensions with other individual student characteristics, such as their perceptions of feedback usefulness.

1.7.3 Study 3 – Exploring Students’ Receptivity to Feedback: A Latent Profile Analysis

Finally, Study 3 adopted a person-centered approach to explore the relationships between RIF profiles and established factors influencing feedback effectiveness. Previous research on RIF predominantly focused on variable-centered approaches (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022). However, different levels of RIF dimensions exhibited by students may not function independently and should thus be considered together. For example, a student may value (instrumental attitudes) and enjoy (experiential attitudes) receiving feedback but still face challenges in implementing it (behavioral engagement). Therefore, complementing a variable-centered approach with a person-centered approach, which considers multiple variables simultaneously, can enhance the understanding of why some students accept and engage with feedback more effectively than others. The aim of this study was to provide a comprehensive representation of RIF profiles by (1) identifying and characterizing RIF profiles, (2) identifying differences in profile membership based on cognitive ability, personality traits, prior achievement, age, and gender, and (3) examining the associations between different RIF profiles and revision performance on a writing task.

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Chapter 2 – Receptivity to Instructional Computer-Based Feedback (RIF): A Multistudy Validation of a German RIF Scale (Study 1)

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Abstract

Feedback can play a pivotal role in learning but is only effective when students use it. However, the use of feedback varies greatly from student to student and these differences must be explained. Hence, the construct receptivity to instructional feedback (RIF) was introduced to assess students' attitudes towards and engagement with human-provided feedback in multiple English-speaking countries. However, RIF scales have not yet been used in computer-based assessment contexts nor in German-speaking countries; their application is thus limited. This study examined an adapted and translated RIF scale using confirmatory factor analysis (CFA) and exploratory structural equation modeling (ESEM). We capitalized on data sets comprising German-speaking university ($N = 464$) and secondary school ($N = 1,207$) students. The bifactor-CFA model showed a good model fit and revealed a general receptivity factor alongside the four specific factors: experiential attitudes, instrumental attitudes, cognitive engagement, and behavioral engagement with feedback. Scalar measurement invariance allowed for cross-gender and educational level comparisons. The relationships with broader personality characteristics were consistent with other contexts, thus indicating discriminant validity. General receptivity, cognitive engagement, and experiential attitudes positively correlated with GPA, suggesting convergent validity. Results support the stability of the RIF scale's adaptation and translation. Assessment implications are discussed.

Keywords: feedback, receptivity, validity evidence, computer-based feedback, measurement invariance

2.1 Introduction

Feedback can play a pivotal role in learning, but it is only effective when students engage with it (Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Wisniewski et al., 2020). Individual levels of feedback receptivity have been shown to relate to differences in recipients' response to and use of feedback in educational psychology (Hedgcock & Lefkowitz, 1994; Lipnevich & Smith, 2022; Panadero & Lipnevich, 2021), industrial and organizational psychology (Linderbaum & Levy, 2010; London & Smither, 2002), and medical psychology (Mills et al., 2023). Therefore, current feedback discussions and models emphasize the central role that receptivity to feedback in the feedback process plays in explaining the differences in feedback effectiveness (Lipnevich & Panadero, 2021). In educational psychology, the construct of receptivity has four theoretically assumed dimensions: behavioral (do I know what to do with feedback?) and cognitive (do I understand feedback?) engagement with feedback, as well as instrumental (do I think feedback is useful?) and experiential (do I like feedback?) attitudes towards feedback (Lipnevich et al., 2021).

Lipnevich et al. (2021) developed and validated a scale in English to measure students' receptivity to instructional feedback (RIF) for feedback from human instructors, such as teachers or professors. However, feedback is increasingly provided in computer-based assessment (Mertens et al., 2022). This may change the social context in which students are confronted with the feedback. Fong and Schallert (2023) pointed out that the social context may be different in computer-based contexts, in which students work alone on tasks without the active involvement of a human feedback provider. For example, students may react with increasing demotivation to negative feedback when it is provided by a computer compared to when it is delivered in person (Fong et al., 2019). Thus, the role of the feedback-providing agent must be acknowledged, and the scale adapted accordingly. Despite the frequent use of adapted (and translated) psychological instruments, their psychometric qualities cannot be assumed to be similar to the standardized versions in the primary language (Gudmundsson, 2009). Hence, scales that are to be used in new contexts (and languages) must be tested for their psychometric qualities (Beaton et al., 2000), their factorial structure (see, e.g., Hofverberg & Winberg, 2020), and for measurement invariance (Leitgöb et al., 2022). Therefore, the major aim of this study was to validate a German version of the scale used to measure RIF in a computer-based assessment context.

2.1.1 Receptivity to Instructional Feedback (RIF)

RIF is a construct that originated in personality psychology and is described as trait-like feedback receptivity (Lipnevich & Lopera-Oquendo, 2022). RIF rests on the assumption that individuals may have varying degrees of willingness or readiness to accept feedback (Lipnevich et al., 2016). While some students might be generally enthusiastic about obtaining feedback, others might not be as receptive (Lipnevich & Lopera-Oquendo, 2022). To discriminate RIF from broader personality traits, Lipnevich et al. (2021) investigated its relations with the Big Five dimensions of personality. The Big Five personality dimensions are conscientiousness, openness, extraversion, agreeableness, and neuroticism. The four receptivity dimensions provided incremental value over and above broader personality characteristics (Lipnevich et al., 2021). Specifically, conscientiousness was strongly associated with all receptivity dimensions. This suggested that self-disciplined, organized, and efficiently working students tend to be more receptive to feedback (McCrae & John, 1992). Neuroticism related negatively to cognitive engagement with feedback, suggesting that self-conscious and impulsive students are less likely to deeply process feedback (Lipnevich et al., 2021). Openness showed positive links with all receptivity dimensions, suggesting that curious students tend to be more receptive to feedback (Lipnevich et al., 2021). Extraversion and agreeableness were only loosely related to RIF. These associations were reassuring as the receptivity dimensions did not solely resemble broader personality dimensions (see also “jingle-jangle fallacy”, Block, 1995); this indicated evidence of discriminant validity (Lipnevich et al., 2021).

Moreover, Lipnevich and Lopera-Oquendo (2022) found that the subscales experiential attitudes and cognitive and behavioral engagement positively predicted student grades. Thus, the convergent validity of the scale was demonstrated for the prediction of important educational outcomes. Overall, the instrument has been shown to be a valid measure of students’ tendency to accept feedback from instructors, such as teachers or university professors (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022).

2.1.2 Measurement Models of RIF

Surprisingly, despite being defined as “a general, trait-like feedback receptivity” (Lipnevich & Lopera-Oquendo, 2022, p. 1), RIF has been modeled solely by its comprising four factors. Specifically, two studies employed confirmatory factor analysis (CFA) in the context of human-provided feedback and their results supported the four-factorial structure (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022). In those studies, 24 out of 36 items assessing the four receptivity factors showed a good model fit, good internal consistency, $.82 < \alpha < .92$, and

high factor correlations, $.76 < r < .90$ and $.69 < r < .79$, respectively (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022). However, investigations of a general receptivity factor are missing. A general factor's existence can be deduced when there are high factor correlations (Morin et al., 2016), as found in the English version of the RIF scale. The examination of a bifactor model can reveal the latent general factor driving these correlations. In bifactor models, the items of the instrument reflect both a general (G-factor) factor that captures all items (general receptivity) and specific (S-factors) factors that reflect variance shared among items that compose subscales (receptivity dimensions) but cannot be explained by the G-factor (Morin et al., 2020). Therefore, while recognizing the importance of the S-factors, the presence of a G-factor must be investigated for RIF in a computer-based assessment context.

Moreover, while acknowledging that CFA is the most common approach used to investigate the factorial structure of psychological instruments, this often does not do justice to the complexity of psychological constructs. CFA only allows the items to load on their predefined factors; however, in psychology as well as other social sciences, most items do not strictly load on their associated factors (Xiao et al., 2019). When assessing RIF, cross-loadings may occur due to the complex and multifaceted nature of feedback receptivity. For example, an item intended to measure the cognitive dimension (e.g., "I know how to use feedback to improve my work") could also relate to the instrumental dimension (e.g., "Feedback is important for my success") because both items, though primarily designed to assess distinct dimensions of feedback receptivity, share underlying themes related to performance outcomes. In essence, the way individuals conceptualize their ability to use feedback (cognitive dimension) is intrinsically linked to their perception of feedback's role in achieving success (instrumental dimension). This interconnectedness between cognitively knowing how to utilize feedback and instrumentally valuing it for success illustrates why an item might cross-load between these two factors. Thus, when items are not allowed to load on factors other than their associated factors, important information can be lost and this, in turn, can be susceptible to distorted factors (Asparouhov & Muthén, 2009). Correspondingly, the exclusion of cross-loadings can modify the meaning of a construct (Asparouhov et al., 2015). Moreover, not allowing cross-loadings can lead to overestimated factor correlations because it forces items to load only on their main factor (Asparouhov & Muthén, 2009). Asparouhov and Muthén (2009) suggested the use of exploratory structural equation modeling (ESEM)—an approach that allows cross-loadings—to better reflect the complexity of psychological constructs. According to simulation studies, ESEM factor correlations tend to be closer to population values than those derived from CFA models (Asparouhov et al., 2015). Hence, ESEM might be especially valuable when assessing

which items to include in a questionnaire as this approach offers a more accurate picture of the relationships between items and factors in the questionnaire validation process. Nonetheless, when choosing a final model, as per Ockham's razor, the more parsimonious (i.e., fewer parameters to estimate) model is considered superior among models that fit equally well.

2.1.3 Purpose of the Present Study

In the present article, we report on an adapted version of the RIF scale to measure RIF in computer-based assessment contexts. We examined the adapted version in samples of German-speaking university and secondary school students and tested the factorial structure. Moreover, we investigated whether the adapted and translated scale measured equally across educational level and gender. Further, we investigated relations with personality traits and GPA to determine the discriminant and convergent validity of our scale. Specifically, we preregistered¹ the following research questions and associated hypotheses:

Research Question 1: Does the adapted German RIF scale show a four-factor subscale structure?

Hypothesis 1 (H1): We expected that the adapted German RIF scale would show a four-factor structure in its subscales.

Research Question 2: Can the measurement model be improved by including the general receptivity factor next to the four factors?

Hypothesis 2 (H2): We expected to find support for a bifactor representation.

Research Question 3: Does the instrument measure equally across educational level and gender?

Hypothesis 3 (H3): We expected the instrument to measure equally across educational level and gender.

Research Question 4: Are the Big Five personality traits related to RIF?

Hypothesis 4: We expected to find relations with the Big Five personality traits similar to those found by Lipnevich et al. (2021). Specifically, we expected conscientiousness to be most strongly related to RIF.

Research Question 5: Does RIF relate to GPA?

¹ The preregistration can be found at <https://osf.io/yvd5q>; deviations at <https://osf.io/mkve7>

Hypothesis 5 (H5): We expected RIF to be positively related to GPA.

2.2 Method

We report how we determined our sample size, all data exclusions (if any), all data inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all measures in the study, and all analyses including all tested models. If we use inferential tests, we report exact p values, effect sizes, and 95% confidence or credible intervals.

2.2.1 Adaptation and Translation Process

First, we adapted the items to match our context (e.g., “I look forward to receiving feedback on my work” instead of “I look forward to receiving the instructor’s comments on my work”). Thereby, we intended to make the measure applicable for the computer-based assessment context. Changes were made to 18 items, while the other 18 items remained unchanged (see Table S1, Supplementary Material). We included all 36 items to assess which items best measured receptivity in a computer-based assessment context.

Second, the authors translated the adapted scale into German. A native English-speaker—not familiar with the instrument—performed a back-translation (in line with the *Guidelines for Translating and Adapting Tests* by the International Test Commission, 2017). The back-translation was compared to the adapted original to ensure that the meaning was comparable. A bilingual group of experts carefully reviewed the quality of the translation and adaptation.

2.2.2 Sample

Sample 1 consisted of 464 university students ($M_{age} = 24.3$, $SD = 4.4$, age range = [18, 58]; 50.4% male, 48.1% female, 1.5% other gender identities) in Germany. They were recruited on Prolific (www.prolific.co) and received €5 for their participation. Prolific is an online participant pool known for high data quality (Palan & Schitter, 2018; Peer et al., 2022). Sample 2 consisted of 1,207 secondary school students ($M_{age} = 16.0$, $SD = 1.4$, age range = [14, 21], 18.1% missing; 35.2% male, 43.8% female, 3.8% other gender identities, 17.2% missing) in Grades 9 ($n = 358$), 10 ($n = 240$), 11 ($n = 310$), 12 ($n = 266$), and 13 ($n = 33$) in Germany. Their participation was voluntary, and they did not receive any compensation. No participants were excluded due to rapid-guessing behavior, which is operationalized by unrealistically low response times (i.e., reading speed faster than 500 words per minute).

2.2.3 Instruments

2.2.3.1 RIF

The RIF scale is a self-report instrument intended to measure students' acceptance of instructional feedback (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022). The items are measured on a five-point scale comprising *strongly disagree* (1), *disagree* (2), *neither* (3), *agree* (4), and *strongly agree* (5). The internal consistency, measured with Cronbach's alpha, for the current sample and the final retained model (18 items) was as follows: For the behavioral engagement subscale (6 items): Sample 1: $\alpha = .88$, Sample 2: $\alpha = .88$; for the cognitive engagement subscale (4 items), Sample 1: $\alpha = .81$, Sample 2: $\alpha = .76$; for the experiential attitudes subscale (5 items): Sample 1: $\alpha = .86$, Sample 2: $\alpha = .83$; and finally, for the instrumental attitudes with feedback subscale (3 items): Sample 1: $\alpha = .84$, Sample 2: $\alpha = .85$. Cronbach's alpha in the English version (24 items) ranged from .82 to .92 (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022). We presented the items in an intermixed format instead of grouping them according to their hypothesized factors, as is done in the original version of the scale, because this has been suggested (at least) for newly developed measures (Goodhue & Loiacono, 2002). Further, the item presentation in an intermixed format has demonstrated superior convergent and discriminant validity (Schriesheim & DeNisi, 1980). Face validity was established by participants confirming that the items were easy to understand and were relevant (Allen et al., 2023).

2.2.3.2 Big Five Personality Inventory

The items measure an individual on the Big Five dimensions of personality (Rammstedt & John, 2005). The items are measured on a five-point scale from *strongly disagree* (1), *disagree* (2), *neither* (3), *agree* (4), to *strongly agree* (5). Cronbach's alpha for the current sample was as follows: For the agreeableness scale: Sample 1: $\alpha = .58$, Sample 2: $\alpha = .58$; for the conscientiousness scale: Sample 1: $\alpha = .75$, Sample 2: $\alpha = .75$; for the extraversion scale: Sample 1: $\alpha = .84$, Sample 2: $\alpha = .64$; for the neuroticism scale: Sample 1: $\alpha = .83$, Sample 2: $\alpha = .74$; and finally, for the openness scale: Sample 1: $\alpha = .73$, Sample 2: $\alpha = .66$. The scale reliabilities in the present study are similar to those reported in the initial validation studies (Kovaleva et al., 2013; Rammstedt & John, 2005).

2.2.3.3 Other Variables

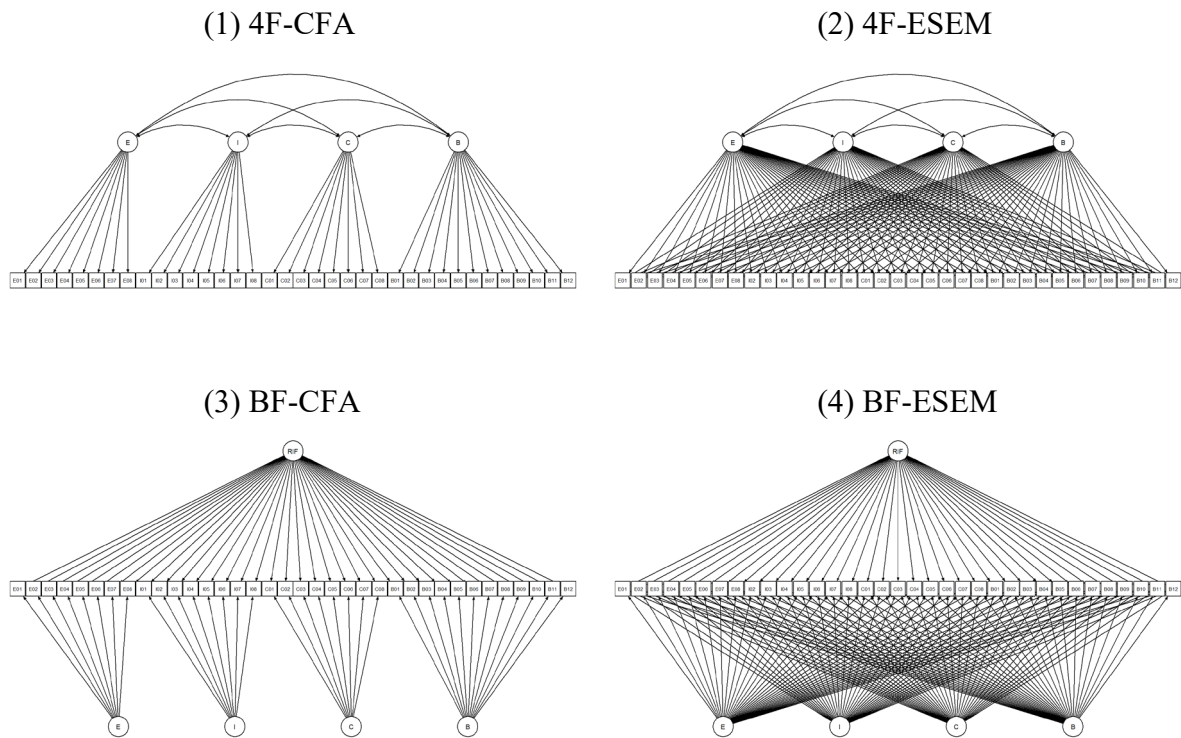
We captured students' age, gender, and GPA. Gender was used for measurement invariance analyses. Moreover, all of these variables were needed to investigate the correlations with the receptivity factors.

2.2.4 Analysis Plan

All analyses were performed in *Mplus* Version 8.8 (Muthén & Muthén, 1998–2017) by means of structural equation modeling. The robust maximum likelihood estimator (MLR) was used for estimation as it offers standard errors and model fit tests that can withstand data nonnormality. This estimator is also favored when there are five or more response categories, as in the RIF scale (Rhemtulla et al., 2012). To test H1, the following two models were estimated: (1) a four-factor CFA model differentiating between experiential attitudes, instrumental attitudes, cognitive engagement, and behavioral engagement, and (2) a four-factor ESEM model allowing freely estimated item loadings on their a priori factors and cross-loadings, using target rotation to have them as close as possible to zero. To test H2, the multidimensional structure of the German version of the RIF was estimated with the following two models: (3) a bifactor-CFA model specifying each item as loading on both its a priori factors and its G-factor, and (4) a bifactor-ESEM model using orthogonal bifactor target rotation specifying all items on the G-factor and the receptivity factors with the identical pattern (target, nontarget loadings, and cross-loadings) as in the ESEM solution (see Fadda et al., 2020; and Lohbeck & Retelsdorf, 2021 for similar approaches). Conceptual representations of the estimated models are set out in Figure 2.1.

Figure 2.1

Conceptual Representations of the Estimated Models



Note. CFA = confirmatory factor analysis; 4F = four-factor; BF = bifactor model; ESEM = exploratory structural equation modeling; E = experiential attitudes subscale; I = instrumental attitudes subscale; C = cognitive engagement subscale; B = behavioral engagement subscale; RIF = general receptivity (G-factor).

The overall model fit for the measurement analyses was evaluated using the comparative fit index (CFI) and the Tucker-Lewis index (TLI), where values greater than .90 were considered to be adequate and values greater than .95 were evaluated as a good model fit (Hu & Bentler, 1999), the root-mean-square error of approximation (RMSEA), where values between .05 and .08 were considered reasonable and values smaller than .05 were considered a good model fit, and the standardized root-mean-square residual (SRMR), where values smaller than .08 were considered a good model fit (Browne & Cudeck, 1992). Furthermore, we considered the chi-square test statistics.

However, the described fit criteria should only serve as rough guidelines. Therefore, in addition, we considered the standardized parameter estimates, statistical conformity, and theoretical adequacy. We used the explained common variance (ECV) to evaluate the proportion of variance in the RIF items that could be attributed to the general factor, compared to the total common variance explained (see Lauriola et al., 2021 for a similar approach). Furthermore, we investigated the reliability of the receptivity factors using omega coefficients. Total omega (ω)

was used to examine the proportion of variance of the total scores that was due to all factors, without differentiating between general and specific factors. Omega hierarchical (ω_h) was used to report on the proportion of variance of the total scores that was due to the general factor, controlling for the variance of the specific factors. Omega coefficients (ω_{sg}) were also computed for the subscales and indicated the proportion of variance of the subscale scores that was due to the S-factor of that subscale (Green & Yang, 2015). To test H3, measurement invariance across educational level and gender, multigroup CFA was used. The measurement invariance was indicated by ΔCFI smaller than 0.010 and $\Delta RMSEA$ smaller than 0.015 (Δ = the changes in CFI/RMSEA; Chen, 2007; Cheung & Rensvold, 2002). To test H4 and H5 and in exploration, the best latent model was retained and correlations with the Big Five personality traits, age, and GPA were examined.

2.3 Results

2.3.1 Measurement Model

We first ran the models with all 36 items and stepwise excluded items that did not meet the cutoff criteria (λ greater than .50 in the 4F-CFA/ESEM). Table 2.1 reports the global fit indices for the tested models with the final 18 items. The four-factor CFA model showed an adequate fit to the data, whereas the bifactor-CFA, the four-factor ESEM, and the bifactor-ESEM models showed a good to excellent fit.

However, as the overall model fit should only serve as a rough guideline, we further inspected the standardized factor loadings of the models under investigation (see Table S2, Supplemental Material). First, the parameter estimates of the four-factor CFA and the four-factor ESEM were compared. The four-factor CFA showed moderate to high factor loadings ($\lambda = [.59, .87]$, $M = .71$) and sufficient composite reliability ($\omega = [.75, .85]$, $M = .81$). The four-factor ESEM showed similar moderate to high factor loadings ($\lambda = [.53, .97]$, $M = .68$) and sufficient composite reliability ($\omega = [.70, .84]$, $M = .79$) with low cross-loadings ($\lambda = [-.16, .18]$, $M = .02$). The latent factor correlations of the four-factor ESEM model were comparable ($.39 \leq r \leq .64$) to those of the four-factor CFA model ($.41 \leq r \leq .71$). Next, the bifactor-CFA model was compared to the bifactor-ESEM model. The bifactor-CFA model showed moderate to high factor loadings ($\lambda = [.25, .71]$, $M = .53$) and high composite reliability ($\omega = .93$ in Sample 1 and $\omega = .92$ in Sample 2) on the G-factor and moderate to high factor loadings ($\lambda = [.25, .83]$, $M = .46$) and sufficient composite reliability ($\omega = [.75, .86]$, $M = .82$) on the S-factors (see Table 2). The bifactor-ESEM model showed small to high factor loadings ($\lambda = [.19, .71]$, $M = .52$) and high composite

reliability ($\omega = .94$ in Sample 1 and $\omega = .92$ in Sample 2) on the G-factor and moderate to high factor loadings ($\lambda = [.27, .87]$, $M = .48$) and sufficient composite reliability ($\omega = [.75, .88]$, $M = .83$) on the S-factors and moderate to low cross-loadings ($\lambda = [-.23, .14]$, $M = .00$).

The bifactor-CFA model was retained for further analyses as the generally low cross-loadings in the ESEM models indicated that the items were not strongly related to multiple factors, which was consistent with the assumptions of the bifactor-CFA model. Choosing the bifactor-CFA model in this case led to a more parsimonious and interpretable solution, as the restricted cross-loadings simplified the factorial structure. Additionally, the bifactor-CFA model might be more stable and easier to estimate, particularly with smaller sample sizes. In the bifactor-CFA model, around half of the common variance was attributed to the general factor (ECV = .58 in Sample 1 and ECV = .53 in Sample 2), while the specific factors accounted for the rest. The proportion of reliable variance in the total score attributed solely to the G-factor (ω_H) was high compared to the total reliable variance (ω). After controlling for the G-factor variance, the ω_{sg} coefficients became low for the behavioral engagement subscale, low to moderate for the cognitive engagement subscale, moderate for the experiential attitudes subscale, and low for the instrumental attitudes subscale (see Table 2.2).

Table 2.1

Model Fits (Grouping Sample)

| Models under investigation | <i>CFI</i> | <i>TLI</i> | <i>SRMR</i> | <i>RMSEA</i> | <i>RMSEA [90% CI]</i> | <i>AIC</i> | <i>BIC</i> | <i>saBIC</i> |
|----------------------------|------------|------------|-------------|--------------|-----------------------|------------|------------|--------------|
| <u>4F-CFA</u> | | | | | | | | |
| Configural | .922 | .907 | .049 | .058 | [.054, .062] | 74,613.45 | 75,263.99 | 74,882.77 |
| Metric | .921 | .911 | .052 | .057 | [.053, .060] | 74,614.15 | 75,188.79 | 74,852.05 |
| Scalar | .917 | .911 | .055 | .057 | [.053, .060] | 74,639.36 | 75,138.11 | 74,845.84 |
| <u>BF-CFA</u> | | | | | | | | |
| Configural | .948 | .932 | .033 | .049 | [.045, .054] | 74,319.58 | 75,100.23 | 74,642.76 |
| Metric | .946 | .938 | .049 | .047 | [.043, .051] | 74,333.08 | 74,945.67 | 74,586.69 |
| Scalar | .944 | .938 | .050 | .047 | [.044, .051] | 74,344.29 | 74,886.41 | 74,568.72 |
| <u>4F-ESEM</u> | | | | | | | | |
| Configural | .956 | .923 | .024 | .053 | [.048, .057] | 74,268.25 | 75,374.17 | 74,726.09 |
| Metric | .955 | .940 | .034 | .047 | [.042, .051] | 74,259.56 | 75,061.89 | 74,591.72 |
| Scalar | .952 | .940 | .036 | .047 | [.042, .051] | 74,273.32 | 74,999.76 | 74,574.06 |
| <u>BF-ESEM</u> | | | | | | | | |
| Configural | .980 | .957 | .016 | .039 | [.034, .045] | 74,033.64 | 75,291.36 | 74,554.33 |
| Metric | .981 | .973 | .026 | .031 | [.026, .036] | 73,984.50 | 74,889.84 | 74,359.30 |
| Scalar | .978 | .970 | .029 | .033 | [.028, .038] | 74,002.11 | 74,836.97 | 74,347.73 |

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root-mean-square residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; AIC = Akaike information criterion; BIC = Bayesian information criterion; saBIC = sample-size-adjusted BIC; CFA = confirmatory factor analysis; 4F = four-factor; BF = bifactor model; ESEM = exploratory structural equation modeling. The 4F-ESEMs were estimated with target oblique rotation. The BF-ESEMs were estimated with bifactor orthogonal target rotation.

Table 2.2

Standardized Factor Loadings (First Value: Sample 1 [University Students], Second Value: Sample 2 [Secondary School Students]) From the Bifactor-CFA Model Including One General and Four Specific Factors

| Item | Item content | G λ | F1 λ | F2 λ | F3 λ | F4 λ | δ |
|-------------------------------|--|----------------|-----------------|-----------------|-----------------|-----------------|----------|
| <u>Behavioral engagement</u> | | | | | | | |
| B01 | When I receive feedback, I carefully read every comment detail | .52/.49 | .44/.49 | | | | .53/.52 |
| B02 | I go over feedback several times | .47/.47 | .56/.55 | | | | .47/.48 |
| B06 | I work through the feedback I receive | .64/.69 | .36/.26 | | | | .46/.46 |
| B08 | I don't really process the feedback I receive | .69/.66 | .28/.25 | | | | .44/.50 |
| B09 | I try to address every detail of the feedback I receive | .57/.61 | .32/.31 | | | | .57/.52 |
| B10 | I only look at feedback quickly | .56/.46 | .44/.53 | | | | .49/.51 |
| <u>Cognitive engagement</u> | | | | | | | |
| C01 | I understand how to use the feedback that I get | .57/.40 | | .40/.48 | | | .51/.61 |
| C04 | I know how to use feedback to improve my work | .67/.55 | | .42/.58 | | | .37/.36 |
| C05 | When I get feedback on an assignment, I know how to work with it | .59/.44 | | .45/.52 | | | .46/.54 |
| C08 | I understand how to use feedback to make my work better | .57/.52 | | .48/.58 | | | .45/.40 |
| <u>Experiential attitudes</u> | | | | | | | |
| E01 | I enjoy learning how well I did on tests or assignments | .38/.25 | | | .68/.57 | | .40/.61 |
| E04 | I do not like when my work is evaluated | .40/.31 | | | .46/.58 | | .63/.57 |
| E05 | I look forward to receiving feedback on my work | .60/.55 | | | .40/.44 | | .48/.51 |
| E07 | I hate it when I receive feedback on the work I have done | .59/.46 | | | .39/.51 | | .50/.53 |
| E08 | I like learning how I did on an assignment | .40/.35 | | | .83/.65 | | .15/.45 |
| <u>Instrumental attitudes</u> | | | | | | | |
| I02 | Feedback is important for my success | .57/.57 | | | | .48/.41 | .45/.51 |
| I04 | Feedback is very effective in helping me enhance my performance | .71/.70 | | | | .41/.37 | .32/.37 |
| I07 | Receiving feedback is the best way to learn | .43/.54 | | | | .49/.32 | .58/.61 |
| ω | | .93/.92 | .86/.85 | .83/.81 | .86/.81 | .78/.75 | |
| ω_H | | .79/.74 | | | | | |
| ω_{Sg} | | | .28/.28 | .29/.46 | .49/.55 | .31/.20 | |

Note. B = behavioral engagement subscale; C = cognitive engagement subscale; E = experiential attitudes subscale; I = instrumental attitudes subscale; F = factor; G = G-factor; ω = Total omega coefficient; ω_h = Hierarchical omega coefficient for G-factor; ω_{sg} = Omega coefficient for S-factors; λ = standardized factor loading; δ = residual variance. Values in bold significant at $p < .000$.

2.3.2 Measurement Invariance

The models tested to establish measurement invariance are reported in Tables 2.1 and 2.3. We considered alternative fit indices (AFIs) such as CFI, TLI, RMSEA, and SRMR, rather than chi-square, as AFIs are considerably less sensitive to sample size (Meade et al., 2008). We first assessed measurement invariance across the sample, then by gender, and finally by both sample and gender.

Across all tested models, the configural invariance models showed a good fit to the data. Hence, we progressively added invariance constraints. With the addition of invariance constraints to the factor loadings, the metric invariance models demonstrated a comparable fit to the data and reached all recommended cutoff scores. Change indices were within the recommended range (ΔCFI smaller than 0.010 and ΔRMSEA smaller than 0.015), thus confirming weak invariance in our models. When adding invariance constraints to the item intercepts, the scalar invariance models displayed a good fit to the data, with change indices within the recommended range. This supports strong invariance in our models.

Table 2.3

Model Fit of the Bifactor-CFA Model (Grouping Gender, and Sample and Gender)

| | <i>CFI</i> | <i>TLI</i> | <i>SRMR</i> | <i>RMSEA</i> | <i>RMSEA [90% CI]</i> | <i>AIC</i> | <i>BIC</i> | <i>saBIC</i> |
|-----------------------------------|------------|------------|-------------|--------------|-----------------------|------------|------------|--------------|
| <u>Grouping gender</u> | | | | | | | | |
| Configural | .951 | .937 | .034 | .049 | [.044, .054] | 62,261.76 | 63,018.05 | 62,560.62 |
| Metric | .949 | .942 | .045 | .047 | [.043, .051] | 62,268.61 | 62,862.09 | 62,503.13 |
| Scalar | .947 | .941 | .048 | .047 | [.043, .051] | 62,280.32 | 62,805.53 | 62,487.86 |
| <u>Grouping sample and gender</u> | | | | | | | | |
| Configural | .946 | .929 | .040 | .052 | [.047, .057] | 61,862.37 | 63,374.96 | 62,460.09 |
| Metric | .942 | .937 | .066 | .049 | [.045, .054] | 61,856.36 | 62,880.51 | 62,261.07 |
| Scalar | .936 | .935 | .070 | .050 | [.046, .055] | 61,866.34 | 62,685.67 | 62,190.11 |

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root-mean-square residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; AIC = Akaike information criterion; BIC = Bayesian information criterion; saBIC = sample-size-adjusted BIC.

2.3.3 Discriminant and Convergent Validity

Descriptive statistics for each sample can be found in Tables S3 and S4 (Supplementary Material). The correlations with personality traits, gender, GPA, and age are shown in Table 2.4. The classification of the strength of the effects was based on the recommendations of Gignac and Szodorai (2016), with .10, .20, and .30 being considered small, medium, and large, respectively. General receptivity was most strongly related with conscientiousness, regardless of educational level or gender. Associations with neuroticism were negative and ranged from small to large. Links with openness became solely significant for secondary school students and were medium to large. Similarly, associations with extraversion and agreeableness were only observed for secondary school students, also ranging from medium to large. Generally, associations with personality traits were larger for female students than for male students across both educational levels.

Table 2.4

Correlations with Personality Characteristics, Age, and GPA

| Scale | General RIF | | | | Behavioral engagement | | | | Cognitive engagement | | | | Experiential attitudes | | | | Instrumental attitudes | | | |
|------------|----------------|---------------|---------------|---------------|-----------------------|-------------|--------------|-------------|----------------------|---------------|---------------|---------------|------------------------|------|--------------|------|------------------------|------|--------|-------------|
| | University | | School | | University | | School | | University | | School | | University | | School | | University | | School | |
| | F | M | F | M | F | M | F | M | F | M | F | M | F | M | F | M | F | M | F | M |
| A | .03 | .11 | .31*** | .14 | .05 | -.03 | -.19* | -.15 | .04 | -.06 | -.23** | -.24** | -.09 | .02 | -.07 | .02 | .03 | -.11 | .00 | .01 |
| C | .62*** | .44*** | .43*** | .33*** | -.19 | -.02 | .12 | .18* | -.05 | .09 | .11 | .04 | -.17* | -.11 | .08 | -.02 | -.32* | .02 | -.03 | .03 |
| E | .14 | .07 | .15* | .18* | -.10 | -.13 | -.13 | -.06 | .01 | .22* | .08 | -.15 | -.17* | -.11 | .08 | -.02 | -.32* | .02 | -.03 | .03 |
| N | -.29*** | -.10 | -.22** | -.21** | .28** | .08 | .16 | .16 | -.20* | -.28** | -.17* | -.10 | -.04 | -.10 | -.07 | .03 | .26* | -.04 | .07 | .28* |
| O | .11 | .02 | .14* | .30*** | .08 | .26* | .10 | .16 | .07 | .26* | .11 | -.01 | -.06 | -.10 | -.06 | .06 | -.04 | .03 | .05 | .05 |
| Age | .26** | .10 | .07 | .17* | -.03 | .08 | -.13 | -.13 | .16 | .23* | -.12 | -.05 | -.05 | .02 | .16** | .10 | -.22 | .07 | .06 | -.10 |
| GPA | .12 | .22* | .26*** | .23** | .02 | -.14 | -.04 | .08 | -.10 | -.12 | .14* | .00 | .05 | -.02 | .16** | .10 | .13 | -.18 | -.04 | -.05 |

Note. F = female; M = male. A = Agreeableness; C = Conscientiousness; E = Extraversion; N = Neuroticism; O = Openness.

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

The correlations of general receptivity with GPA ranged from .12 to .26, with significant positive relations found for female university students and male university and secondary school students on the general factor. Unique aspects of cognitive engagement and experiential attitudes had small positive relations with GPA for female school students.

2.4 Discussion

Given the great variety in feedback effectiveness (Wisniewski et al., 2020), more research is needed to determine the role that individual student characteristics play in the feedback process (Panadero & Lipnevich, 2021). RIF can help to explain why some students benefit from feedback, while others do not. To investigate these differences, a sound instrument is needed. Therefore, in the current study, we provide validity evidence for an adapted and translated version of the RIF scale for researchers working with computer-based assessment in German-language areas. We investigated the measurement model of our scale and measurement invariance across educational level and gender, and we obtained discriminant and convergent validity evidence. Overall, we interpret our results as a successful validation of the adapted German RIF scale. The scale can now be used in future studies.

In line with H1, the results support the theoretical dimensions of receptivity and align with previous findings. We found four factors, representing the dimensions of experiential attitudes towards feedback, instrumental attitudes towards feedback, cognitive engagement with feedback, and behavioral engagement with feedback. Hence, the specific factors established when assessing RIF for human-provided feedback held for computer-generated feedback (Lipnevich et al., 2021, Lipnevich & Lopera-Oquendo, 2022). Thus, the adaptation of the scale from the context of human- to computer-provided feedback was successful.

In line with H2, we found a G-factor next to the four S-factors. This result contributes to the theoretical discussion of the construct as it indicates that there might be a higher-order construct that underlies and drives the correlation between the RIF's S-factors. The G-factor represents the variance shared among all items, while the S-factors represent additional variance shared only among items that compose subscales and that cannot be explained by the G-factor (Morin et al., 2020). Thus, the G-factor represents the general receptivity, and the S-factors represent distinct dimensions of receptivity. The G-factor accounted for about half of the common variance, while the S-factors accounted for the remaining half. This means that including the G-factor can improve the statistical power in studies investigating the relations between RIF and learning outcomes. Although the G-factor plays a significant role, the S-factors still had a substantial combined influence in the model. Despite the high factor loadings of the S-factors, which indicated their validity, the high hierarchical omega coefficients for the G-factor suggested that the interpretation of the findings should be focused on the G-factor instead of the S-factors. Future studies should investigate the presence of a general factor when assessing

receptivity even when the feedback is provided in traditional assessment contexts (i.e., with a human feedback-providing agent). This would strengthen the theoretical understanding of the construct and could enhance the utility and interpretability of the measurement scale, bolster RIF's predictive power, and contribute to the development and refinement of theory. Therefore, our findings regarding the general factor's theoretical contribution significantly extend beyond the technical aspects of the scale validation.

Employing CFA and ESEM models in the stepwise exclusion of items towards our final set of 18 items resulted in well-defined factors with negatable cross-loadings. This was especially visible when considering the similar interfactor correlations in the four-factor CFA and four-factor ESEM models. The low cross-loadings in the ESEM models suggested that the items were not strongly related to multiple factors. Thus, the bifactor-CFA model provided a parsimonious and interpretable solution, for researchers and educators alike.

In line with H3, we established strong measurement invariance across educational level and gender. Hence, we enhanced comparability and reduced measurement bias and can confidently interpret differences observed in the data as reflective of true differences between groups. This, in turn, strengthens the overall validity of the adapted RIF scale.

In line with H4, the relations we found between general receptivity and broader personality traits were comparable to those found in previous research; this indicates the stability of these relations across contexts (see Lipnevich et al., 2021). Specifically, conscientiousness was most strongly related with students' general receptivity, regardless of educational level or gender. Moreover, we found that the associations of conscientiousness and neuroticism with general receptivity were similar across educational levels, while the relationships between all other personality traits and general receptivity diminished from secondary to postsecondary education. The observed variations in the strength of the relationships between general receptivity and personality traits across educational levels correspond with research on the connections between personality traits and academic performance (see Mammadov, 2022; Poropat, 2009). Given the association of receptivity and academic performance, this is not surprising.

In line with H5, we provide convergent validity evidence as we found significant moderate positive relations of general receptivity with GPA for male university and female and male school students. Unique aspects of cognitive engagement and experiential attitudes had small positive relations with GPA for female school students. This corresponds with findings from the secondary school context on instructor-provided feedback that revealed the predictive value

of experiential attitudes for student grades (Lipnevich & Lopera-Oquendo, 2022). These results are very promising in terms of the practical value of the RIF construct, especially because conscientiousness, one of the strongest predictors of academic achievement, on average, shows comparable relations with GPA ($\rho = 0.28^2$; Meyer et al., 2023).

2.4.1 Limitations

It is possible that our Prolific sample differs from a sample collected in person at a university. That is, the composition of personality traits in a sample of clickworkers might not reflect that of a sample collected in person at a university (see, e.g., Colman et al., 2017). Rapid-guessing behavior was not observed in our samples as the time spent on task was as expected, which suggests that our samples were highly engaged; in the university sample, monetary incentives may have contributed to this because we informed participants that the payment depended on thorough and honest answering. Nevertheless, the results of our investigation could be replicated using a sample collected in person at a university.

Furthermore, we relied solely on self-reported grades; this can be problematic. Kuncel et al. (2005) found that self-reported grades tend to be fairly accurate representations of actual grades for high-achieving students with good GPAs. However, for students with lower GPAs, self-reported grades may not accurately reflect their actual performance. Hence, future studies should investigate associations with actual achievement, such as revision performance.

To make the scale available to researchers in the context of computer-based assessment and in German, we had to both adapt and translate the scale. This may have resulted in us finding other items than those in the original version of the scale. However, some of the items (see Table S1, Supplementary Material) that were only translated (and were not adapted) did not assess receptivity in our context very well (i.e., $\lambda < .50$). Thus, some items appear to be context-dependent. Insights from all application contexts should be combined to select fewer items, which could result in a questionnaire that is valid for the assessment of receptivity across contexts.

2.4.2 Practical Implications

The proposed translation and adaptation of the scale can be used in computer-based assessment contexts and in German-language areas. The average processing time of less than 3 minutes can be considered extremely economical. When RIF is measured in a computer-based assessment context, it should be measured with 18 items (for the German items, see Table S1,

² ρ = mean correlation corrected for measurement error

Supplementary Material). The code and data are available in the project's OSF register (<https://osf.io/mkve7>).

2.4.3 Conclusion

This study successfully validated an adapted German version of the RIF scale for computer-based assessment. Our findings supported the four theoretical subfactors of receptivity, confirmed the presence of a general receptivity factor, established strong measurement invariance across gender and educational levels, and provided additional discriminant and convergent validity evidence. This suggests that the adapted RIF scale can be confidently used in German-speaking contexts, providing a valuable tool for researchers and educators in assessing students' feedback receptivity in computer-based environments and ultimately supporting the quest to unlock the full potential of feedback as a catalyst for student achievement and development.

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Chapter 3 – How Receptivity to Instructional Feedback (RIF) Relates to Revision Performance and Task Interest: The Role of Perceived Feedback Usefulness (Study 2)

Bahr, J. L., Höft, L., Meyer, J., Schaller, N. J., & Jansen, T. (2025). *How Receptivity to Instructional Feedback (RIF) Relates to Revision Performance and Task Interest: The Role of Perceived Feedback Usefulness*. Manuscript submitted for publication.

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Abstract

Background: Feedback can have a pivotal influence on writing performance and task interest, but its effectiveness varies widely across students. Feedback models suggest that students' trait-like receptivity to instructional feedback (RIF) and state-like perceptions of feedback usefulness explain these individual differences; however, empirical investigations in authentic feedback contexts are lacking.

Aims: We investigated whether specific RIF dimensions were associated with increased revision performance in a writing task and with higher task interest, and whether these relations were mediated by perceptions of feedback usefulness.

Sample: 1,507 secondary school students ($M_{age} = 16.4$, $SD = 1.4$) in Germany participated.

Methods: Students wrote an argumentative text, received feedback, and revised their texts. Structural equation models were conducted to investigate our research questions.

Results: We found direct effects for two RIF factors—behavioral engagement and instrumental attitudes—on students' revision performance. Additionally, we found a direct effect of one RIF factor—general receptivity—on changes in task interest. Our results showed no significant indirect effects of RIF factors on revision performance via perceived usefulness. However, results showed a full mediation of the effect of general receptivity on changes in task interest via perceived usefulness.

Conclusions: Students' trait-like behavioral engagement and instrumental attitudes are of particular importance for improving revision performance, whereas mediating state-like perceptions of feedback usefulness are important for explaining the relation between general receptivity and increased task interest. Our findings underscore the importance of considering both trait-like RIF and state-like perceptions to explain why some students benefit more from feedback than others.

Keywords: receptivity to instructional feedback, perceived usefulness, interest, performance, individual differences

3.1 Introduction

Fostering argumentative writing is one of the central goals of K-12 science education in order to prepare students for meaningful participation in socio-scientific discourses (Osborne & Pimentel, 2022). Feedback can have a pivotal influence on writing performance (Graham et al., 2015; 2023; 2024) and interest (Camacho et al., 2021) but the effects differ between studies and students (Wisniewski et al., 2020). For decades, researchers have attempted to explain the variability in the effectiveness of feedback for learning (Hattie & Timperley, 2007; Kluger & DeNisi, 1996).

Panadero and Lipnevich proposed an integrative model (2022) based on the history of educational feedback theorization (for their review of feedback models and theories, see Lipnevich & Panadero, 2021) that aimed to explain the variability in feedback effectiveness for both performance and motivational outcomes. In their model, individual student characteristics and perceptions, rather than the content of feedback, are central in determining the effectiveness of feedback; the model reflects the current paradigm shift in feedback research towards studying how feedback is received and used (Winstone & Nash, 2023). A fundamental component within this new paradigm is the idea of feedback literacy; which conceptualizes the understanding, capacities, and dispositions needed in order for students to engage in feedback (Carless & Boud, 2018; Dawson et al., 2023; Molloy et al., 2020; Nieminen & Carless, 2022).

Feedback literacy is shaped by both students' trait-like characteristics and their state-like perceptions of specific feedback. Trait-like individual differences in feedback reception, termed receptivity to instructional feedback (RIF), capture students' tendencies to accept feedback (Lipnevich et al., 2021). This multidimensional construct comprises students' general receptivity ("am I willing and ready to accept feedback?") to feedback as well as specific behavioral ("do I know what to do with feedback?") and cognitive engagement ("do I understand feedback?") with feedback, and their instrumental ("do I think feedback is useful?") and experiential ("do I like feedback?") attitudes towards feedback (Bahr et al., 2024; Lipnevich et al., 2021). Students with higher levels on RIF dimensions tend to perceive feedback as more useful, engage with it more actively, internalize its content, and apply it to improve their performance (Lipnevich & Lopera-Oquendo, 2022). While empirical studies have shown positive associations between RIF dimensions and academic performance (e.g., Bahr et al., 2024; Lipnevich & Lopera-Oquendo, 2022), none have examined these trait-like tendencies together with students' state-like perceptions in real-world feedback settings. This gap is notable, as it raises two possibilities: that trait-like RIF dimensions directly relate to changes in

performance and interest, or that these relations are mediated by state-like perceptions of feedback usefulness.

Our study addressed this gap by examining the relation between students' trait-like RIF and their state-like perceptions of feedback usefulness in the context of argumentative writing. Specifically, we investigated whether trait-like RIF dimensions relate to revision performance and task interest, and if these relations are mediated by state-like perceptions of feedback usefulness. To address these questions and enhance our understanding of feedback literacy, we provided computer-based feedback to a large sample of secondary school students.

3.1.1 Feedback and its Effects on Performance and Interest

In our study, we followed the definition of Lipnevich and Panadero (2021):

Feedback is information that includes all or several components: students' current state, information about where they are, where they are headed and how to get there, and can be presented by different agents (i.e., peer, teacher, self, task itself, computer). This information is expected to have a stronger effect on performance and learning if it encourages students to engage in active processing. (p. 25)

The fundamental purpose of feedback is to bridge the gap between students' current understanding and the desired learning goal (Bangert-Drowns et al., 1991; Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Narciss, 2008). Effective feedback addresses three core questions posed by Hattie and Timperley (2007): (1) *Where am I going?* (goals, feed-up); (2) *How am I going?* (progress, feed-back); and (3) *Where to next?* (strategy, feed-forward). To trigger students' situational task interest, feedback should include a few specific, actionable suggestions (Renninger & Hidi, 2022). This approach not only supports task completion but also bolsters motivation and fosters a sense of competence (Narciss, 2008).

In addressing the first question, *Where am I going?* it is important to clarify learning goals and assessment criteria, establishing clear performance expectations (Reddy & Andrade, 2010). For instance, in argumentative writing, students need to articulate a clear point of view (i.e., a major claim, Osborne et al., 2016), which should be made explicit in the feedback message. The second question, *How am I going?* requires assessing student performance. Feedback is most effective when it not only assesses but also explains the assessment, helping students identify and correct errors or misunderstandings (Rich et al., 2017). For example, feedback might highlight a missing major claim as an area for improvement. Finally, addressing *Where to next?* involves providing forward-looking guidance (Sadler, 2010), including specific strategies or

examples to help learners achieve their goals (see Table S1 for examples of feedback messages related to these three questions, Supplementary Material).

Empirical research has consistently shown that feedback is a powerful influence on student learning. Meta-analyses of studies that focused on fostering writing, reported medium effect sizes ranging from $d = 0.30$ to $d = 0.38$ (Graham et al., 2015; 2023; 2024). Further, Fleckenstein et al. (2023) also specifically looked at the effects of automated computer-based feedback on writing performance and found a medium effect size of $g = 0.55$, ranging from -1.73 to 2.99. Fleckenstein et al. (2023) also pointed out that automated feedback should not be considered a universal solution as its impact varies depending on individual student characteristics. Regarding the effects of feedback on motivation, Wisniewski et al. (2020) found a medium effect size of $d = 0.33$, ranging from 0.23 to 0.42, across domains and feedback agents (i.e., the feedback-providing source).

3.1.2 Receptivity to Instructional Feedback (RIF)

A pivotal student disposition addressed in Panadero and Lipnevich's feedback model is RIF (e.g., Lipnevich et al., 2016; Panadero & Lipnevich, 2022). RIF has its roots in personality psychology and can be defined as trait-like feedback receptivity (Lipnevich & Lopera-Oquendo, 2022). The theory is based on the understanding that individuals can differ in their capability and willingness to accept feedback (Lipnevich et al., 2016). For instance, some students may appreciate receiving feedback in any academic setting, while others may be more reluctant to accept it (Lipnevich & Lopera-Oquendo, 2022). RIF is a multidimensional construct comprising a general receptivity dimension and four discrete subdimensions, each delineating a specific aspect of feedback receptivity. These include behavioral and cognitive engagement with feedback, as well as instrumental and experiential attitudes towards feedback (Bahr et al., 2024; Lipnevich et al., 2021).

Studies have shown positive associations between RIF dimensions and student learning outcomes, with students' general receptivity ($r = .22$ to $r = .26$ in Bahr et al., 2024), behavioral engagement ($\beta = 0.075$, $SE = 0.04$, $p < .05$ in Lipnevich & Lopera-Oquendo, 2022), cognitive engagement ($r = .14$ in Bahr et al., 2024; $\beta = 0.041$, $SE = 0.02$, $p < .05$ to $\beta = 0.073$, $SE = 0.03$, $p < .05$ in Lipnevich & Lopera-Oquendo, 2022), experiential attitudes ($r = .16$ in Bahr et al., 2024; $\beta = 0.038$, $SE = 0.02$, $p < .05$ to $\beta = 0.070$, $SE = 0.03$, $p < .05$ in Lipnevich & Lopera-Oquendo, 2022), and instrumental attitudes ($\beta = 0.036$, $SE = 0.02$, $p < .05$ to $\beta = 0.055$, $SE = 0.03$, $p < .05$ in Lipnevich & Lopera-Oquendo, 2022) all linked to academic performance, such as grade point average (GPA). Although the relations between trait-like RIF dimensions and

improvements in revision performance and task interest have not yet been examined in an authentic feedback setting, it is reasonable to assume that students who like receiving feedback (experiential attitudes), think it is important for their success (instrumental attitudes), understand the feedback and have strategies to comprehend and master the feedback (cognitive engagement), act upon it (behavioral engagement), and are competent in dealing with feedback (general receptivity) benefit more from feedback than those who do not. Thus, trait-like RIF dimensions may shape the effectiveness of feedback, leading to greater improvements in writing performance and higher task interest—potentially through students' state-like perception of feedback usefulness.

3.1.3 Perceptions of Feedback Usefulness

As illustrated above, limited research has examined how trait-like RIF dimensions influence students' inclination to accept and use feedback in an ecologically valid performance setting. However, a body of research suggests that students' state-like perceptions—their "perceived usefulness of feedback"—play a crucial role in feedback engagement and effectiveness. Students are thought to evaluate feedback based on its perceived usefulness, comparing it to their current understanding and performance (Bouwer & Dirks, 2023). This evaluative process helps them decide whether and how to use the feedback to improve their work, as they make judgments about its relevance and value (Boud et al., 2018; Carless & Boud, 2018; Nicol, 2021). These judgments influence how feedback is applied in revisions (Bouwer & Dirks, 2023), as students are more likely to engage with feedback they find useful (Ilgen et al., 1979; Jansen et al., 2025; Jonsson & Panadero, 2018; Lipnevich & Smith, 2009). The perception of feedback usefulness has been linked to improvements in both performance and task interest (Harks et al., 2014; Rakoczy et al., 2013; 2019).

In two studies examining the perception of feedback usefulness, students received written feedback on a mathematics task. After an instructor explained the feedback's structure and content, students were given an additional 10 minutes to review it independently, and then rated its perceived usefulness. These studies found that perceived usefulness was positively related to both performance ($\beta = .20$, 95% *CI* [.04, .35]; $\beta = .57$, 95% *CI* [.18, 1.08], respectively) and interest ($\beta = .21$, 95% *CI* [.03, .40]; $\beta = .52$, 95% *CI* [.17, .91], respectively; Harks et al., 2014; Rakoczy et al., 2013). In another study, students rated the feedback's usefulness after a 13-week intervention; perceived usefulness was associated with changes in interest ($\beta = 0.146$, *SE* = 0.04, $p < .001$) but not in performance ($\beta = -0.042$, *SE* = 0.04, $p = .349$; Rakoczy et al., 2019). These findings suggest that perceived usefulness may enhance students' sense of competence,

which could drive greater motivation and persistence in tasks. In turn, this may support improved performance and increased interest over time (see Harks et al., 2014; Sansone, 1986).

Although students' state-like perceptions of feedback usefulness have been a key focus in feedback research (Van der Kleij & Lipnevich, 2021), their relation with trait-like characteristics remains unclear. Research has yet to explore whether state-like perceptions of feedback usefulness might help explain how trait-like RIF dimensions can lead to greater performance and increased task interest. The potential mediating role of perceived feedback usefulness in this process has not yet been investigated (see call for research; Van der Kleij & Lipnevich, 2021).

3.1.4 Present Study

The purpose of the present study was to investigate how students' trait-like RIF dimensions and their state-like perceptions of feedback usefulness contribute to the effectiveness of feedback in a revision process. To this end, students wrote an argumentative essay and revised it using computer-delivered feedback messages targeting one of four key learning goals identified for the task (see Section 2.3). We measured students' changes in writing performance and their changes in task interest. The hypothesized relations are depicted with solid lines in the model in Figure 1. Specifically, we had the following research questions:

H1a–e: Are students' (a) general receptivity, (b) behavioral engagement, (c) cognitive engagement, (d) instrumental attitudes, and (e) experiential attitudes related to positive changes in their performance?

H2a–e: Are students' (a) general receptivity, (b) behavioral engagement, (c) cognitive engagement, (d) instrumental attitudes, and (e) experiential attitudes related to positive changes in their task interest?

We expected positive relations between all RIF dimensions and both performance and motivational outcomes. Additionally, we investigated whether the relation between trait-like RIF dimensions and feedback outcomes might be mediated by state-like perceptions of feedback usefulness. Specifically, we explored whether students with higher levels on RIF dimensions would perceive the same feedback as more useful than students with lower receptivity. This hypothesized mediation is denoted by dotted lines in Figure 3.1. We used mediation analyses to investigate the following research questions:

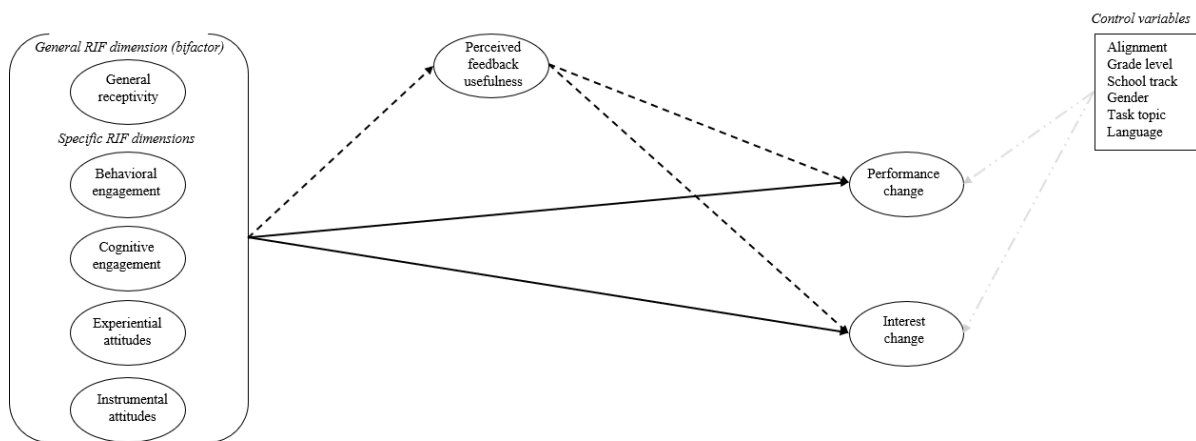
H3a–e: Are the relations of students' (a) general receptivity, (b) behavioral engagement, (c) cognitive engagement, (d) instrumental attitudes, and (e) experiential attitudes to changes in their performance mediated by their perception of feedback usefulness?

H4a–e: Are the relations of students' (a) general receptivity, (b) behavioral engagement, (c) cognitive engagement, (d) instrumental attitudes, and (e) experiential attitudes to changes in their task interest mediated by their perception of feedback usefulness?

We expected that students' state-like perceptions of feedback usefulness would mediate the relations between all trait-like RIF dimensions and both performance and motivational outcomes.

Figure 3.1

Hypothesized Path Model



Note. Solid lines denote H1a–e and H2a–e, dotted lines denote H3a–e and H4a–e, and grayed mixed lines indicate potential relations between control variables and both outcomes.

3.2 Method

3.2.1 Transparency and Openness Statement

The data, code, and outputs are available at <https://osf.io/xm827>. 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.

3.2.2 Design and Sample

In the study, 1,507 students ($M_{age} = 16.4$, $SD = 1.4$, age range = [14, 21], 17.2% missing; 42.8% female, 36.2% male, 4.4% diverse, 16.7% missing) from 26 academic secondary schools (equivalent to grammar schools or high schools; "Gymnasium" in Germany, $n = 1,014$) in Grades 9 ($n = 299$), 10 ($n = 256$), 11 ($n = 225$), 12 ($n = 211$), and 13 ($n = 23$) and 10 nonacademic secondary schools (equivalent to vocational and comprehensive schools; "Berufsschule" and "Gemeinschaftsschule" in Germany, $n = 493$) in Grades 9 ($n = 47$), 10 ($n = 72$), 11 ($n = 195$), 12 ($n = 118$), and 13 ($n = 61$) participated. By including a wide range of grade levels, we aimed to capture a diverse sample that reflects various stages of educational development. This diversity enhances the generalizability of our findings across grade levels. Importantly, the tasks were carefully designed to be manageable and appropriate for students across all grade levels, ensuring that each student could engage with the materials meaningfully and without undue difficulty.

3.2.3 Procedure

The study was conducted in the students' usual classrooms during regular class time and all materials were provided in German language within a digital learning environment accessed with standard web browsers. The students navigated through a series of web pages one after the other, without the option to skip pages or return to previous pages. On the introduction page, the students saw information about the purpose of the study, the procedure, and the privacy measures taken to protect their data. Specifically, students were told that they would be asked to write an essay and would receive feedback after 15 minutes of writing. This would be followed by a 10-minute revision period in which they could use this feedback to improve their writing. In the following sections, grade-level data were collected, and students were asked to fill in the RIF questionnaire. After that, students looked at the writing task and rated their interest in the 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 task for possible policy support. 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 S2, Supplementary Material). The topic of the task was assigned randomly.

During the writing process, students were given materials with information for and against each option to guide their writing process. After writing their first draft, students were asked again to rate their interest in the task. Then, the students were informed again that they would have an additional 10 minutes to revise their texts and were instructed to utilize the feedback they would receive. Following this instruction, students received one of four predetermined feedback messages, each designed to target higher-order concerns addressing one of four key hints for writing a good text (Table S1, Supplementary Material, see Keller et al. [2024] for a similar feedback scheme). Students were unaware that the feedback provided in the study was predetermined and presumably believed it was an immediate response to their drafts. After receiving the feedback, students rated the usefulness of the feedback and commenced the process of revising their texts (see Table S3 for illustrative examples of student draft texts, received feedback, and revised text, Supplementary Material). After the revision, students were asked again to rate their interest in the topic. At the end, students were asked to provide demographic data (language most spoken at home, school type, and gender).

3.2.4 Measures

3.2.4.1 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). The items are measured on a five-point scale ranging from 1 = *strongly disagree* to 5 = *strongly agree* (see Table S4 for all items, Supplementary Material). In computer-based assessment contexts, RIF is measured with 18 items and best conceptualized with a bifactor-CFA model (Bahr et al., 2024). In the current study, the general factor explained about half of the common variance ($ECV = .64$), while the remaining half was accounted for by the specific factors. Cronbach's alpha was as follows: For the behavioral engagement subscale (6 items, e.g., "I work through the feedback I receive."): $\alpha = .84$; for the cognitive engagement subscale (4 items, e.g., "I understand how to use feedback to make my work better."): $\alpha = .81$; for the experiential attitudes subscale (5 items, e.g., "I look forward to receiving feedback on my work."): $\alpha = .79$; and, finally, for the instrumental attitudes subscale (3 items, e.g., "Feedback is important for my success."): $\alpha = .75$.

3.2.4.2 Perceived Feedback Usefulness

Perceived feedback usefulness was assessed with the subscale "usefulness" from a German version of the Feedback Perceptions Questionnaire (FPQ; Strijbos et al., 2010). The scale consists of three items (e.g., "I consider this feedback useful."). The participants rated each item on a 10-point visual analog scale ranging from 1 = *fully disagree* to 10 = *fully agree* (see Table

S5 for all items, Supplementary Material). The FPQ was recently validated and its measurement invariance regarding gender, school type, and year of study was ensured (Strijbos et al., 2021). For the current sample, the Cronbach's alpha was $\alpha = .95$.

3.2.4.3 Situational Interest Change

Triggered situational interest was assessed with the scale "catch" from a German version of the Situational Interest Questionnaire (Knogler et al., 2015). The scale consists of three items that capture student emotion (e.g., "I enjoyed the task.") and three items that capture student attention (e.g., "The task was able to capture my attention."). The participants rated each item on a five-point rating scale ranging from 1 = *not at all* to 5 = *very much* (see Table S6 for all items, Supplementary Material). The scale draws upon theoretical assumptions of situational interest (Geyer, 2008; Hidi & Renninger, 2006; Lewalter & Geyer, 2009). For the current sample, the Cronbach's alphas were $\alpha = .94$ for T1 and $\alpha = .94$ for T2. The change in interest from T1 to T2 was measured using latent change score modeling with strict measurement invariance (Goodness-of-fit statistics of the unconditional latent change score model: comparative fit index [CFI] = .991, Tucker-Lewis index [TLI] = .989, root-mean-square error of approximation [RMSEA] = .035, standardized root-mean-square residual [SRMR] = .022; see Table S7, Supplementary Material). We defined M-1 correlated method factors (M-1 approach) to account for method effects (Geiser & Lockhart, 2012).

3.2.4.4 Performance Change

Performance change was determined in three steps. First, students' written texts were annotated by trained raters (for an in-depth description of the rater training and the text annotation process, see Jansen et al., 2025; Schaller et al., 2024), who assessed the texts regarding the following eight text quality indicators, each with their own scale: *Accuracy* indicates if an argument is scientifically correct, incorrect, or unrelated to the material (Heitmann et al., 2014). *Adequacy* indicates if an argument is relevant, irrelevant, or unrelated to the assignment (Heitmann et al., 2014). *Content zones* indicate the position of structural parts of the text, for example, introduction, main part, and conclusion (Stede et al., 2015). *Major claim* refers to the author's final position on the given topic, if a major claim exists, and if its position in the text is marked (Stab & Gurevych, 2014). *Toulmin's argumentation pattern* identifies the parts of an argument: claim, data, warrant, and rebuttal (Osborne et al., 2016; Wilson et al., 2023). *Use of options for action* describes whether an argument is for or against one of the three options listed in the task or whether the stance is unclear. *Use of criteria* provided in the material identifies which of the six criteria from the material are discussed in an argument. *Decision-making strategy* indicates which strategy is taken to justify the major claim. The three strategies are unfounded, cutoff,

and trade-off (Eggert & Bögeholz, 2009; Sakschewski et al., 2014). The intraclass correlation coefficients as a measure of interrater reliability were similar to other state-of-the-art text corpora (e.g., Crossley et al., 2022; Rupp et al., 2019) and can be found in Table S8 (Supplementary Material). The correlation among the eight text quality indicators can be found in Tables S9 and S10 (Supplementary Material).

All eight text quality indicators are integral to our aggregate measure because argumentative writing performance involves more than the four learning goals emphasized in our feedback messages (see Section 2.3.). For example, an argumentative essay must also include an introduction, body, and conclusion (*Content zones*), the arguments made must be drawn from the material we provided (*Use of criteria*), be scientifically accurate (*Accuracy*), and be relevant (*Adequacy*). The learning goals outlined in our feedback messages were directly related to *Major claim*, *Toulmin's argumentation pattern*, *Use of options for action*, and *Decision-making strategy* (see Table S1, Supplementary Material).

Second, we applied a many-facet Rasch model (MFRM; for a detailed introduction to the model, see Gordon et al., 2021) separately for T1 (i.e., draft text) and T2 (i.e., revision text), using the R package TAM (Robitzsch et al., 2022) to obtain person ability scores. The robust Haerbara method was used to link the two estimated models (Kolen & Brennan, 2014; Gonzales & Wiberg, 2017). The MFRM is a well-known logit model (Linacre, 1989), with the log-odds of the ratings as the outcome and multiple facets as predictors. Using the MFRM model, item difficulties can be recorded on a metric scale with the WLE as an estimator of the person parameters (standardized to an average item difficulty of 0). In our application, the eight text quality indicators were modeled as items with steps, and we included facets for the raters and tasks. All interactions between items, steps, raters, and tasks were allowed to model severity/leniency tendencies. EAP/PV and WLE were used to estimate person ability parameters, with reliability values greater than .70 considered adequate (Bond & Fox, 2007). In addition, the estimated WLE scores were used as an indicator of performance. In the current study, the MFRM showed an acceptable fit to the data, with an expected a posteriori/plausible value (EAP/PV) reliability of .79 and .80 and a WLE reliability of .82 and .83, respectively (Bond & Fox, 2007).

Third, performance change from T1 to T2 was calculated using latent change score modeling (Goodness-of-fit statistics of the unconditional latent change score model: CFI = .995, TLI = .995, RMSEA = .061, SRMR = .049) based on the weighted likelihood estimated (WLE) scores.

3.2.4.5 Control Variables

We included gender (0 = male, 1 = female), school track (0 = nonacademic, 1 = academic), grade level, students' language background (0 = other, 1 = German), and task topic (0 = automotive energy, 1 = power source) as control variables.

3.2.4.5.1 Feedback Alignment

In our study we used one out of four predetermined feedback messages (see Table S1 for examples of feedback messages and their relation to the three questions of Hattie & Timperley [2007], Supplementary Material), each addressing one of the four learning goals (Table S1, Supplementary Material, see Keller et al. [2024] for a similar feedback scheme). To accurately account for the alignment between the students' draft performance at T1 and the predetermined feedback message they received, we checked whether the learning goal outlined in the given feedback message had already been fulfilled in the students' draft. This alignment was coded dichotomously. Specifically, if a student received the feedback message related to the *Major claim*, we examined whether their draft text included a major claim. If the feedback pertained to *Use of options for action*, we checked whether each argument in the draft contained all three specified options for action. For feedback on *Toulmin's argumentation pattern*, we checked whether each argument contained a warrant. Lastly, for the feedback *Decision-making strategy*, we determined whether the draft featured a trade-off. In our analysis we included the alignment (0 = learning goal fulfilled, 1 = learning goal not fulfilled) as a control variable and further added group membership (i.e., the four different feedback messages) as a dummy variable. Robustness checks using alternative evaluations of alignment demonstrated that these different operationalizations did not alter the relations under investigation (see S11, Supplementary Material).

3.2.5 Analysis Plan

All analyses were performed in *Mplus* Version 8.8 (Muthén & Muthén, 1998–2017) by means of structural equation modeling. The maximum likelihood estimator (ML) with bootstrap (BS) was used for estimation. We used the *type = complex* option in *Mplus*. This option adjusts the standard errors of parameter estimates to account for the nonindependence of observations within clusters, thereby providing robust parameter estimates and standard errors.

We estimated 95% confidence intervals (CIs) for the effects, and we computed standard errors of indirect effects through a bootstrapping procedure with 5,000 samples because we analyzed indirect effects (i.e., products of direct paths) and the distribution of the product terms was only asymptotically normal (Shrout & Bolger, 2002). We report CIs instead of significance levels

for all effects of the path analysis as these have been shown to be rather trustworthy (Hayes & Scharkow, 2013). An indirect effect was present if zero was not included in the CI. The classification of the strength of the effects was based on the recommendations of Gignac and Szodorai (2016), with .10, .20, and .30 being considered small, medium, and large, respectively.

The overall model fit for the measurement analyses was assessed using CFI and TLI, with values greater than .90 considered adequate and values greater than .95 considered good model fit (Hu & Bentler, 1999), RMSEA, with values between .05 and .08 considered adequate and values less than .05 considered good model fit, and SRMR, with values less than .08 considered good model fit (Browne & Cudeck, 1992).

To address our research questions, the structural equation models displayed in Figures 2 and 3 were applied to the data. To test our hypotheses, we looked at the direct effects of general receptivity, behavioral engagement, cognitive engagement, instrumental attitudes, and experiential attitudes on students' changes in performance (H1a–e) and in interest (H2a–e). Further, we looked at the indirect effects of general receptivity, behavioral engagement, cognitive engagement, instrumental attitudes, and experiential attitudes on students' changes in performance (H3a–e) and interest (H4a–e) via perceived feedback usefulness.

3.3 Results

Means, standard deviations, and the correlations of all variables in the mediated structural equation model analysis (see Figure 3.3) are depicted in Table 3.1. We used full information maximum likelihood to handle missing data. In all our analyses we controlled for draft performance at T1 and interest at T1 (see the project's OSF folder [<https://osf.io/xm827>] for full scripts and outputs of all our reported analyses).

Table 3.1

Descriptive Statistics

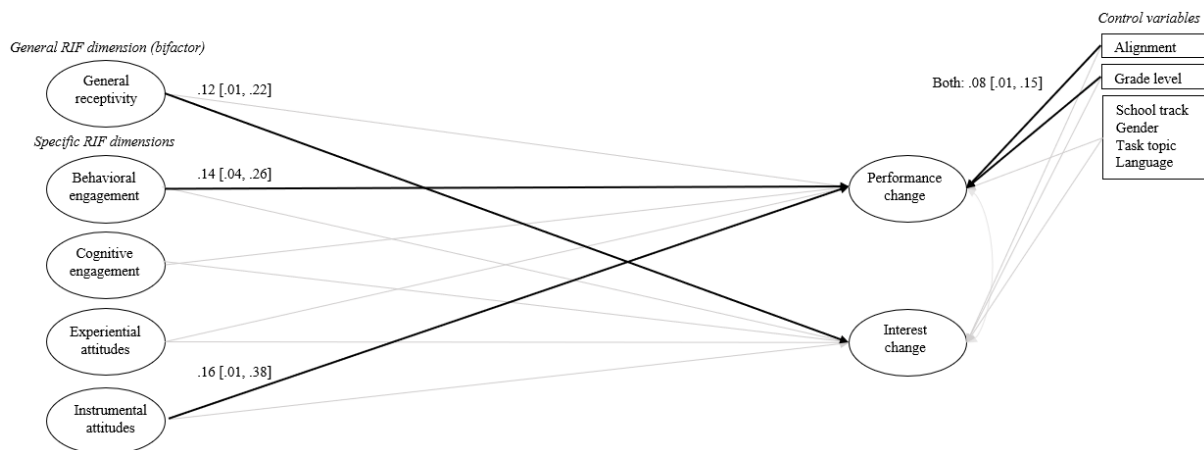
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | <i>M</i> | <i>SD</i> |
|---------------------------|-------|---------|--------|------|--------|--------|--------|--------|--------|--------|--------|-----|--------|------|----------|-----------|
| 1. Gender | | | | | | | | | | | | | | | 0.54 | 0.50 |
| 2. School track | .01 | | | | | | | | | | | | | | 0.67 | 0.47 |
| 3. Grade level | .04 | -.29*** | | | | | | | | | | | | | 10.65 | 1.21 |
| 4. Age | -.01 | -.33*** | .78*** | | | | | | | | | | | | 16.37 | 1.44 |
| 5. Language | .04 | .07* | .01 | -.03 | | | | | | | | | | | 0.83 | 0.37 |
| 6. Behavioral Engagement | .08** | .05 | .00 | -.03 | -.08** | | | | | | | | | | 3.18 | 0.89 |
| 7. Cognitive Engagement | -.03 | .01 | .01 | .00 | -.03 | .45*** | | | | | | | | | 3.68 | 0.75 |
| 8. Experiential Attitudes | .00 | .04 | .03 | .01 | -.01 | .40*** | .35*** | | | | | | | | 3.94 | 0.81 |
| 9. Instrumental Attitudes | .04 | -.01 | .07** | .05 | -.05 | .57*** | .48*** | .45*** | | | | | | | 3.67 | 0.87 |
| 10. Interest T1 | -.07* | .06* | .00 | .01 | .09** | .27*** | .25*** | .24*** | .28*** | | | | | | 3.03 | 1.08 |
| 11. Interest T2 | -.04 | .02 | -.02 | -.04 | .05 | .26*** | .21*** | .22*** | .26*** | .79*** | | | | | 2.95 | 1.00 |
| 12. Perceived Usefulness | .00 | -.02 | -.01 | .00 | -.06* | .22*** | .18*** | .16*** | .25*** | .33*** | .41*** | | | | 4.70 | 2.64 |
| 13. Performance T1 | .06* | .10*** | .01 | -.04 | .08** | .05 | .09** | .09** | .05 | .14*** | .03 | .02 | | | -0.03 | 0.70 |
| 14. Performance T2 | .06* | .11*** | .07* | -.01 | .12*** | .11*** | .09*** | .09** | .10*** | .17*** | .08** | .05 | .70*** | | 0.17 | 0.70 |
| 15. Alignment | .04 | .01 | -.02 | .00 | .04 | .04 | .00 | .01 | .00 | -.02 | .03 | .02 | -.07* | -.01 | 0.71 | 0.45 |

Note. Gender (0 = male, 1 = female); school (0 = nonacademic, 1 = academic); language (0 = other, 1 = German); * $p < .05$; ** $p < .01$; *** $p < .001$.

Figure 3.2 depicts the direct effects of the RIF factors on students' changes in performance and in task interest. The model showed a good fit to the data ($\chi^2[710, N = 1,507] = 2,180.55, p < .001$; CFI = .947; TLI = .941; SRMR = .038; RMSEA = .037). The results showed small to medium direct effects of behavioral engagement with feedback and instrumental attitudes towards feedback on students' revision performance (H1b, and e), whereas general receptivity, cognitive with feedback, and experiential attitudes towards feedback were unrelated to changes in performance (H1a, c, and d). Further, the results showed a small direct effect of general receptivity on changes in interest (H2a), whereas all other RIF factors were unrelated to changes in interest (H2b–e).

Figure 3.2

Simplified Structural Equation Model Depicting the First Tested Model with Direct Effects



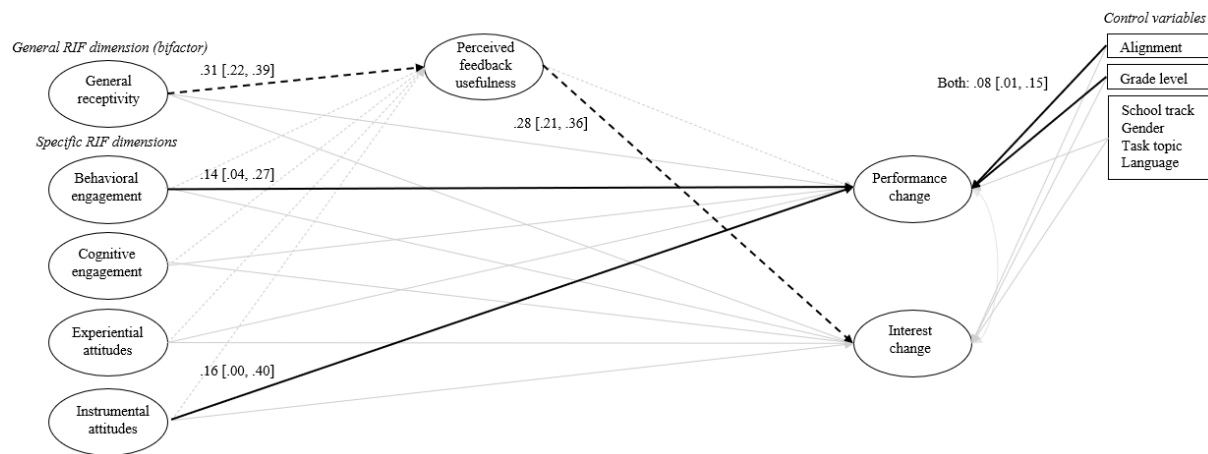
Note. Coefficients presented here are standardized linear regression coefficients with 95% CI in brackets. Paths that are grayed out denote nonsignificant relationships. Proportion of variance explained for each outcome: Performance change, $R^2 = .21$; Interest change, $R^2 = .19$.

Figure 3.3 depicts the direct effects of the RIF factors and students' perceptions of feedback usefulness on students' changes in performance and in interest (see Table 3.2 for indirect effects and CIs; and Table S12 in the Supplementary Material for the full results). The model also showed a good fit to the data ($\chi^2[819, N = 1,507] = 2,092.85, p < .001$; CFI = .955; TLI = .950; SRMR = .035; RMSEA = .032). The results showed no indirect effects of any RIF factors on students' revision performance (H3a–e) via perceived usefulness. Concerning H4a, the results showed a full mediation of the effect of general receptivity on interest change via situational perceived usefulness. Further, the results showed no indirect effects of the other RIF factors on students' change in interest (H4b–e) via perceived usefulness. Among the control variables, alignment and grade level showed small direct effects on changes in performance but not on

changes in interest. The remaining control variables showed no associations with either outcome (see S13, Supplementary Material for further analyses on students' language background).

Figure 3.3

Simplified Structural Equation Model Depicting the Second Tested Model with Direct Effects



Note. Coefficients presented here are standardized linear regression coefficients with 95% CI in brackets. Paths that are grayed out denote nonsignificant relationships. Proportion of variance explained for each outcome: Performance change, $R^2 = .22$; Interest change, $R^2 = .26$.

Table 3.2

Total, Indirect, and Direct Effects of General Receptivity, Behavioral Engagement, Cognitive Engagement, Instrumental Attitudes, and Experiential Attitudes on Revision Performance and Task Interest Change via Perceived Feedback Usefulness

| | Performance change | | | Interest change | | |
|-------------------------------|--------------------|--------|-----|-----------------|--------|-----|
| | | 95% CI | | | 95% CI | |
| | β | LL | UL | β | LL | UL |
| <u>General receptivity</u> | | | | | | |
| Total | .03 | -.07 | .12 | .14 | .04 | .25 |
| Indirect | .01 | -.01 | .05 | .09 | .06 | .13 |
| Direct | .01 | -.09 | .11 | .06 | -.07 | .16 |
| <u>Behavioral engagement</u> | | | | | | |
| Total | .14 | .04 | .26 | .05 | -.06 | .15 |
| Indirect | .00 | -.01 | .00 | -.00 | -.03 | .03 |
| Direct | .14 | .04 | .27 | .05 | -.06 | .15 |
| <u>Cognitive engagement</u> | | | | | | |
| Total | .03 | -.05 | .13 | -.04 | -.15 | .08 |
| Indirect | -.00 | -.01 | .00 | -.01 | -.04 | .02 |
| Direct | .04 | -.05 | .14 | -.03 | -.15 | .09 |
| <u>Instrumental attitudes</u> | | | | | | |
| Total | .16 | .00 | .39 | .04 | -.15 | .25 |
| Indirect | .00 | -.02 | .01 | .01 | -.05 | .06 |
| Direct | .16 | .00 | .40 | .03 | -.17 | .27 |
| <u>Experiential attitudes</u> | | | | | | |
| Total | .03 | -.05 | .12 | .05 | -.05 | .13 |
| Indirect | .00 | -.01 | .00 | -.00 | -.03 | .02 |
| Direct | .03 | -.05 | .12 | .05 | -.04 | .14 |

Note. Coefficients presented here are standardized linear regression coefficients. LL= lower limit, UL= upper limit.

3.4 Discussion

Drawing on Panadero and Lipnevich's (2022) feedback model, this study aimed to examine the relation between students' trait-like RIF and their state-like perceptions of feedback usefulness in the context of argumentative writing. We tested the hypothesis that students with higher levels on RIF dimensions would derive greater benefits from feedback in terms of both revision performance and task interest, and that these associations would be mediated by students' perceptions of the usefulness of task-specific feedback. In doing so, we sought to deepen our understanding of how students' trait-like characteristics and state-like perceptions of specific feedback contribute to feedback literacy. By considering both trait-like RIF and state-like perceptions of feedback usefulness, we explained more variance in our outcomes than by accounting for the receptivity disposition alone. Our findings, which are generalizable across writing tasks and feedback messages, further support the shift in feedback research toward feedback literacy, emphasizing student characteristics over feedback content.

Regarding our first set of hypotheses (H1a–e), we showed that in an ecologically valid setting where feedback was provided that could be used to improve performance in the upcoming revision, students who generally tended to act on feedback (behavioral engagement) and find feedback important (instrumental attitudes) showed higher revision performance in writing (H1b, and e). Students' general receptivity (shared aspects across RIF dimensions), their cognitive engagement (mental strategies learners use to comprehend and master feedback), and their experiential attitudes (whether they like receiving feedback or not) were not related to higher revision performance on a specific argumentative writing task (H1a, c, and d).

Thus, these results can be interpreted as additional evidence that the behavioral engagement and instrumental attitudes dimensions of RIF are related to performance outcomes. This follows on from previous research (Bahr et al., 2024; Lipnevich & Lopera-Oquendo, 2022) that has examined this at a different level of analysis (i.e., for an aggregate measure [GPA]) and found positive associations. It could be expected that trait-like RIF might have larger effects on cumulative measures, as it is reflected in many situations, and thus the modest effect sizes found in this study might accumulate.

Regarding our second set of hypotheses (H2a–e), we found that students' general receptivity was related to increased task interest (H2a). However, students' specific behavioral and cognitive engagement, as well as their experiential and instrumental attitudes, were not related to positive changes in interest (H2b–e). One potential explanation for this finding is that general receptivity reflects students' overall competence in dealing with feedback. Consequently,

students with high levels of general receptivity may be more competent in dealing with the concrete suggestions provided by the feedback, which could in turn lead to increased task interest (see Renninger & Hidi, 2022).

With regard to our third set of hypotheses (H3a–e), we found no evidence of indirect effects of any RIF dimension on students' revision performance via perceptions of feedback usefulness. In other words, the associations between RIF dimensions and students' revision performance were not explained by perceptions of usefulness. Consequently, students who consistently act upon feedback (behavioral engagement) and find feedback important (instrumental attitudes) were able to enhance their performance during the revision process, regardless of whether the feedback was perceived as useful. This suggests that although students with high levels of behavioral engagement and instrumental attitudes do not necessarily perceive feedback as more useful, they may be more responsive to feedback that is not perceived as useful than students with low levels of behavioral engagement and instrumental attitudes.

In a similar vein, the perception of feedback usefulness alone was not found to be related to any changes in performance in the revision. Consequently, the perception of feedback as useful does not necessarily imply that students utilize it. It is also possible that students may find it challenging to assess whether feedback is beneficial to them. This could explain why only Harks et al. (2014) and Rakoczy et al. (2013) found a positive relation between students' perceptions of feedback usefulness and performance. In their studies, an instructor explained the structure and content of the feedback before students rated its usefulness. In our study and in the study of Rakoczy et al. (2019), however, this explanation was absent, thus leaving the students to evaluate the feedback independently. This suggests that the positive associations observed in the two studies may have been influenced by the additional explanations provided, rather than the perception of feedback usefulness.

However, in comparison to the domain of secondary-level mathematics, it might be more challenging for students to determine whether feedback is of use to them in the context of argumentative writing. This is because the identification of errors is often ambiguous, and solution processes do not proceed in a systematic manner (see Harks et al., 2014; Rakoczy et al., 2013; 2019). Consequently, further research is required to examine the role of perceived usefulness in determining performance in various educational domains (see also the call for research; Van der Kleij & Lipnevich, 2021).

Regarding our fourth set of hypotheses (H4a–e), we found that the effect of students' general receptivity on changes in interest was fully mediated by situational perceptions of feedback

usefulness (H4a). This means that the direct effect of students' general receptivity on changes in interest that was investigated in our second hypothesis (H2a) disappeared when perceptions of usefulness were accounted for. This is consistent with findings from other studies that have examined perceptions of usefulness in feedback situations (Harks et al., 2014; Rakoczy et al., 2013; 2019). Thus, changes in task interest are strongly related to students' perceptions of the usefulness of the feedback they receive while working on the task.

3.4.1 Implications for Theory and Practice

Our findings provide a new perspective on the discussion of feedback literacy. By considering both trait-like RIF and state-like perceptions of feedback usefulness, we were able to explain more variance in our outcomes than by examining receptivity alone. This suggests that RIF may indeed represent a fundamental disposition affecting students' willingness to engage with feedback. However, it has also been argued that the ideas of RIF and feedback literacy have very different conceptual bases (Dawson et al., 2023). This, in turn, largely depends on how feedback literacy itself is defined (for a critical review of the emerging concept of feedback literacy, see Nieminen & Carless, 2022).

Moreover, our findings underscore the explanatory power of students' RIF in determining feedback effectiveness, particularly when students receive actionable feedback to improve their writing. Assessing students' RIF in studies on feedback effectiveness could, therefore, offer valuable insights into which types of students are most likely to benefit from feedback interventions. To further understand variations in feedback effectiveness, future research might explore the role of RIF as a function of feedback characteristics.

The hypothesized model that guided this study may need to be modified based on our findings. Specifically, we did not find support for the mediating role of perceived usefulness in the relation between RIF dimensions and performance outcomes. Thus, the assumption that the effect of students' general tendencies in dealing with feedback exerts its influence via the perception of the usefulness of the feedback given on the task at hand was not supported. However, regarding the relation between RIF dimensions and motivational outcomes, the inclusion of perceived feedback usefulness benefited our hypothesized model and improved the proportion of explained variance in both outcomes. Therefore, we believe that our hypothesized model can continue to help other researchers investigate individual differences in feedback effectiveness when studying trait and state-like constructs.

Our findings regarding perceived feedback usefulness call into question its value as a predictor of performance change. Although perceived usefulness is often implemented in learning environments as a single-item indicator of feedback quality (see Meurers et al., 2019), researchers and designers of such environments should be cautious in assuming that it will lead to performance outcomes. However, the strong association with student task interest found in our and other studies (Harks et al., 2014; Rakoczy et al., 2013; 2019) suggests that it may indeed be a good indicator of whether students recognize concrete suggestions for improvement (see Renninger & Hidi, 2022).

3.4.2 Limitations

The feedback messages in our study were not tailored to individual students, and individualized feedback might have resulted in better perceptions of usefulness and more changes in students' writing behavior. Despite this approach, we accounted for the alignment between the students' draft performance at T1 and the predetermined feedback message they received. Our analysis showed that this alignment did not alter the relations we were studying. Nonetheless, we observed a discrepancy between what we defined as useful (i.e., alignment) and what students perceived as useful ($r = .02$, see Table 1). For example, even when feedback was aligned—outlining a learning goal not yet fulfilled in the essay—students did not always perceive it as useful. This highlights a potential misalignment between educator-defined usefulness and student-perceived usefulness. Research supports this complexity; Meyer et al. (2024) demonstrated that even with presumably better aligned, LLM-generated feedback, student perceptions of usefulness varied ($M = 3.72$, $SD = 1.56$ on a 7-point scale). While their usefulness ratings were slightly higher than ours ($M = 4.70$, $SD = 2.64$ on a 10-point scale), ratings in both studies hovered around the midpoint. Even when feedback is provided by a teacher and its structure and content are explicitly explained to students, educator-defined usefulness and student-perceived usefulness do not perfectly align ($M = 2.26$, $SD = 0.55$ on a 4-point scale, Harks et al., 2014; Rakoczy et al., 2013). These findings suggest that alignment between educator-defined and student-perceived usefulness may not always be achievable. Furthermore, this misalignment might explain the limited number of studies demonstrating associations between student perceptions of feedback usefulness and performance outcomes (see Panadero & Lipnevich, 2022; Van der Kleij & Lipnevich, 2021). Nevertheless, given that LLM-generated feedback was rated as somewhat more useful, future studies could investigate its potential to narrow the gap between educator-defined and student-perceived usefulness.

Moreover, the purpose of our study was to examine how students' trait-like RIF was related to performance and motivational outcomes; thus, we measured students' RIF at the beginning of our intervention. Therefore, we cannot infer whether RIF might also be a function of the feedback provided; future research could investigate this. Finally, we only examined a single feedback situation. Longitudinal research is needed to examine the effects of students' RIF across feedback situations. This could also shed light on the trait-like nature of RIF.

3.5 Conclusion

This study highlights the value of integrating students' trait-like RIF with state-like perceptions of feedback usefulness to better understand the impact of feedback on revision performance and task interest. We provided empirical evidence that students' behavioral engagement and instrumental attitudes toward feedback are linked to improved revision performance, independent of how useful they perceive the feedback. Conversely, we found that students' general receptivity to feedback enhances their task interest, mediated entirely by their perception of feedback usefulness. This suggests that RIF dimensions play distinct roles: behavioral engagement and instrumental attitudes directly support revision performance, while perceptions of feedback usefulness mediate the effect of general receptivity on task interest. This highlights the need to prioritize students' feedback literacy, beyond focusing solely on feedback content, to more effectively address the relation between individual differences and feedback outcomes.

3.6 References

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Chapter 4 – Exploring Students’ Receptivity to Feedback: A Latent Profile Analysis (Study 3)

Bahr, J. L., Höft, L., Lipnevich, A. A., Meyer, J., & Jansen, T. (2025). Exploring Students’ Receptivity to Feedback: A Latent Profile Analysis. *Assessment in Education: Principles, Policy & Practice*. Advance online publication. <https://doi.org/10.1080/0969594X.2025.2467676>

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Abstract

A comprehensive understanding of why feedback benefits some students and not others is still lacking. We performed a latent profile analysis of students' receptivity to instructional feedback (RIF) in a sample of 1,800 secondary school students in 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-centered approach compared to a variable-centered approach often used in past research.

Keywords: feedback, receptivity to instructional feedback, latent profile analysis, individual differences, personality

4.1 Introduction

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 et al., 2016; Lipnevich & Smith, 2022; Murano et al., 2021), extensive research has been devoted to understanding factors that influence students' receptivity to feedback, emphasizing 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).

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-centered approaches (Bahr et al., 2024; Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022), 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-centered approach with a more person-centered 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 characterizing 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).

4.1.1 Profile-Defining Construct: Dimensions of Receptivity to Instructional Feedback

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 noncognitive factors that relate to feedback effectiveness could help to explain differences in students' feedback receptivity profiles.

4.1.2 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 (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 hypothesized to predict RIF as well (Panadero & Lipnevich, 2022). Although a few studies have investigated the association of RIF with personality traits in variable-centered 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 subdimensions, 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 organizational 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.

4.1.3 Present Study

In this study we aimed to identify and characterize 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 socio-scientific 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 utilized to enhance students' argumentative writing skills and overall academic performance.

4.2 Method

4.2.1 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.

4.2.2 Design and Sample

1,800 students (age: $M = 16.37$, $SD = 1.47$, range = [14, 21], 17.2% missing; gender: 42.8% female, 36.2% male, 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; "Gemeinschaftsschule" 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.

4.2.3 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 15 minutes to write a draft and were provided with information in favor 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).

4.2.4 Instrumentation

4.2.4.1 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 conceptualized with a bifactor-CFA model, which can capture the latent construct of general receptivity (Bahr et al., 2024). This modeling 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.

4.2.4.2 Cognitive Ability

We measured students' cognitive abilities utilizing the nonverbal figural analogies' subscale of a cognitive abilities test (KFT-R; Heller, 2000) and applied a multigroup IRT model to estimate WLE scores representing students' general cognitive ability score (EAP/PV reliability = .84, WLE reliability = .79) on the same metric. Students had eight minutes to answer as many of the 25 multiple choice items as possible. The instruction students received to fill in the

questionnaire and the associated example items can be found in Table S3 (Supplementary Material).

4.2.4.3 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).

4.2.4.4 Other Variables

We included students' gender³ (0 = male, 1 = female), age, GPA, and school track (0 = nonacademic, 1 = academic).

4.2.4.5 Revision Performance Change

Revision performance change from T1 to T2 was calculated using latent change score modeling (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).

4.2.5 Analytic Plan

All analyses were conducted in *Mplus* 8.7 (Muthén & Muthén, 1998-2017) with nonnormality 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

³ 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 be likely to 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.

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).

4.3 Results

Means, standard deviations, reliabilities, and intercorrelations of all variables are summarized in Table 4.1. The bifactor-CFA model demonstrated a good fit to the data ($\chi^2[117, N = 1,800] = 643.47, p < .001$; RMSEA = .050; CFI = .944; TLI = .927; SRMR = .032).

Table 4.1

Means, Standard Deviations, Reliabilities, and Latent Correlations of Variables

| Measure | <i>M</i> | <i>SD</i> | 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*** |

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

Table 4.2

Model Fit Indices for Different Profile Solutions

| Model | AIC | BIC | saBIC | Entropy | LMR | Profile sizes |
|-------------------|-----------------|-----------------|-----------------|-------------|------------------|------------------------|
| 1 profile | 20501.76 | 20556.72 | 20524.95 | | | 1,800 |
| 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 |

Note. 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.

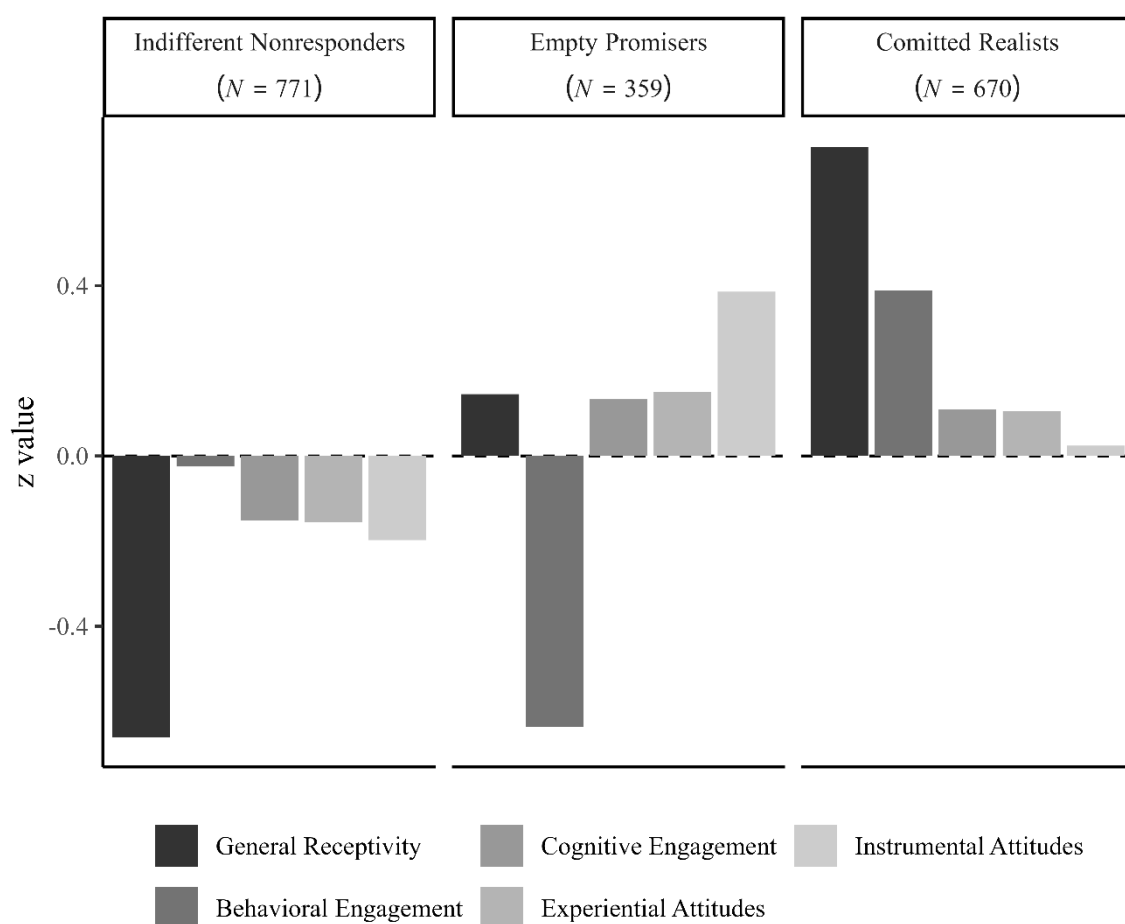
Model fit indices for the different profile solutions are set out in Table 2. The AIC and BIC decreased consistently from one-profile to the five-profile solution, suggesting better fit with more profiles. Similar to AIC and BIC, saBIC also decreased as the number of profiles increased. Entropy increased 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 nonsignificant LMR values and extremely small class sizes. Thus, the three-profile model was considered optimal.

Figure 4.1 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 labeled the profiles *Indifferent 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 general receptivity and cognitive engagement, and held average experiential and instrumental attitudes towards receiving feedback.

Figure 4.1

Z-standardized Mean Scores per Profile for the Three-profile Solution



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 4.3. Compared to students associated with the *Indifferent Nonresponders* profile, those categorized 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 categorized 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 4.3

Results of Multinomial Logistic Regressions for the Effects of Predictors on Profile Membership

| Model | Nonreference profiles | | | |
|--|----------------------------------|--------------------------|------------------------|-------------|
| | <i>Indifferent Nonresponders</i> | | <i>Empty Promisers</i> | |
| | Est. [95% CI] | OR [95% CI] | Est. [95% CI] | OR [95% CI] |
| Reference profile <i>Empty Promisers</i> | | | | |
| 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] | | |

| Model | Nonreference profiles | | | |
|---|----------------------------------|--------------------------|-----------------------------|---------------------------|
| | <i>Indifferent Nonresponders</i> | | <i>Empty Promisers</i> | |
| | Est. [95% CI] | OR [95% CI] | Est. [95% CI] | OR [95% CI] |
| Reference profile <i>Committed Realists</i> | | | | |
| 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] |

Note. 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 categorized 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: $\chi^2 = 11.90, p = .003$).

4.4 Discussion

The purpose of this study was threefold. First, we aimed to identify and characterize 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 characterized by low levels of behavioral engagement whereas *Committed Realists* had high levels of behavioral engagement. This finding underscores the limitations of traditional approaches and emphasizes 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-centered 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 categorized 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) hypothesized 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 utilization is often considered a powerful tool for enhancing academic achievement. This finding appears to contrast with previous studies using a variable-centered 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-centered 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 utilize 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, characterized 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-centered approach. In contrast to previous findings from a variable-centered 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 behavioral 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 seemed to experience 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 utilization (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 emphasize feedback as a tool that enhances their agency and capacity to use it effectively (Jensen et al., 2021). On the basis of 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 toward 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.

4.4.1 Limitations

Some limitations must be considered when interpreting and generalizing 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, personalized 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 generalizability 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 toward 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).

4.5 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 et al., 2016; Lipnevich & Smith, 2022; 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.

4.6 References

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Chapter 5 – General Discussion

5.1 Summaries of the Three Empirical Studies of this Dissertation

5.1.1 Summary of Study 1 – Receptivity to Instructional Computer-Based Feedback (RIF): A Multistudy Validation of a German RIF Scale

The construct of RIF was initially developed to measure students' attitudes toward and engagement with feedback provided by humans across multiple English-speaking countries. However, RIF scales had not yet been applied in computer-based assessment contexts or within German-speaking countries, limiting their broader applicability. Therefore, Study 1 of this dissertation adapted and translated the RIF scale using confirmatory factor analysis (CFA) and exploratory structural equation modeling (ESEM) with data from German-speaking university ($N = 464$) and secondary school students ($N = 1,207$). The bifactor-CFA model demonstrated a good fit and identified a general receptivity factor alongside four specific factors: experiential attitudes, instrumental attitudes, cognitive engagement, and behavioral engagement with feedback. Scalar measurement invariance enabled comparisons across gender and educational levels. The relations between RIF and broader personality traits aligned with findings from other contexts, supporting discriminant validity. Additionally, general receptivity, cognitive engagement, and experiential attitudes were positively associated with GPA, providing evidence for convergent validity. Thus, the first study affirmed the reliability of the adapted and translated RIF scale.

5.1.2 Summary of Study 2 – How Receptivity to Instructional Feedback (RIF) Relates to Revision Performance and Task Interest: The Role of Perceived Feedback Usefulness

In a computer-based writing context, Study 2 investigated whether specific dimensions of RIF were associated with improved revision performance in a writing task and greater task interest, and whether these associations were mediated by students' perceptions of feedback usefulness. The study included a large sample of 1,507 secondary school students in Germany ($M_{age} = 16.4$, $SD = 1.4$). Students wrote an argumentative essay, received automated computer-based feedback, and revised their work. Structural equation modeling was used to analyze the data. The results revealed direct effects of two RIF dimensions—behavioral engagement and instrumental attitudes—on students' revision performance. Additionally, general receptivity directly influenced changes in task interest. While no significant indirect effects of RIF dimensions on revision performance through perceived feedback usefulness were found, the effect of general receptivity on changes in task interest was fully mediated by perceived usefulness. These findings suggest that trait-like behavioral engagement and instrumental

attitudes are critical for enhancing revision performance, whereas state-like perceptions of feedback usefulness explain the association between general receptivity and increased task interest. The results underscore the importance of both stable RIF traits and dynamic perceptions in determining why some students benefit more from feedback than others.

5.1.3 Summary of Study 3 – Exploring Students’ Receptivity to Feedback: A Latent Profile Analysis

Study 3 of this dissertation analyzed the RIF of 1,800 secondary school students in Germany ($M_{age} = 16.37$, $SD = 1.47$) using latent profile analysis. The analysis identified distinct RIF profiles, examined how established factors that relate to feedback uptake (cognitive ability, personality traits, prior achievement, age, and gender) predicted profile membership, and assessed the relations between profile membership and revision performance in writing. Three profiles emerged, characterized by varying levels of behavioral and cognitive engagement with feedback, experiential and instrumental attitudes toward feedback, and general receptivity: *Indifferent Nonresponders*, *Empty Promisers*, and *Committed Realists*. The least successful profile, *Indifferent Nonresponders*, was linked to lower cognitive ability, lower agreeableness, and higher neuroticism. These findings highlight the value of a person-centered approach, which focuses on individual patterns of receptivity, compared to the variable-centered approaches used in Studies 1 and 2.

5.2. Research Question 1

RQ1: How does students’ receptivity to instructional feedback relate to other individual characteristics important for the reception and agentic use of feedback?

This dissertation’s first central research question addressed the associations between RIF and established individual characteristics critical for the reception and agentic use of feedback. These characteristics—student perceptions, cognitive ability, personality traits, prior achievement, age, and gender—are identified in the guiding MISCA model (Panadero & Lipnevich, 2022). To address this question, the present research employed both variable- and person-centered approaches. The variable-centered approach examined associations between the RIF dimensions, while the person-centered approach identified subgroups of students with similar patterns across these dimensions.

Studies 1, 2, and 3 collectively advanced the understanding of how RIF relates to other student characteristics identified in the MISCA model (Panadero & Lipnevich, 2022) and the

implications of these relations for feedback processes. Consistent with prior research (Lipnevich et al., 2021), the findings showed that conscientiousness was the most robust correlate of general receptivity, reflecting its stability across educational contexts. Neuroticism also showed consistent associations, while the links between other personality traits and general receptivity were weaker at higher educational levels—a pattern that mirrors trends in academic performance research (Mammadov, 2022; Poropat, 2009).

The studies also clarified the role of prior achievement and cognitive ability. Study 1 found moderate positive associations between general receptivity and GPA among male university students and female and male secondary school students, with smaller associations observed for female students in terms of cognitive engagement and experiential attitudes. These results align with prior evidence suggesting that female students may benefit more from feedback in computer-based assessment contexts and may generally exhibit higher receptivity (Narciss et al., 2014; Timmers et al., 2015; Lipnevich & Lopera-Oquendo, 2022). In contrast, Study 3's person-centered approach revealed no significant link between GPA and RIF profile membership, potentially due to the heterogeneous composition of the profiles, such as the *Committed Realists* profile, which combined high general receptivity with lower cognitive engagement and experiential attitudes.

A key contribution of Study 2 was the integration of both stable (i.e., RIF dimensions) and situational (i.e., perceptions of usefulness) factors, which demonstrated that general receptivity significantly predicted students' perceptions of feedback usefulness. Notably, perceptions of usefulness fully mediated the relation between general receptivity and interest, emphasizing the dynamic interplay between stable traits and situational states, as outlined in the MISCA model (Panadero & Lipnevich, 2022). Study 3 extended these findings by identifying three distinct RIF profiles—*Indifferent Nonresponders*, *Empty Promisers*, and *Committed Realists*—and exploring how cognitive ability, personality traits, and demographic factors predicted profile membership. Students with higher cognitive ability, higher agreeableness, and lower neuroticism were more likely to belong to the *Committed Realists* or *Empty Promisers* profiles, both of which reflected greater receptivity to feedback. Neuroticism, which is linked to sensitivity to criticism (Brockner et al., 1987; Servaas et al., 2013), predicted membership in the least receptive profile, *Indifferent Nonresponders*. Higher cognitive ability, which is associated with better feedback processing and working memory (Fyfe et al., 2015), and agreeableness, which is tied to cooperative and trusting dispositions, were associated with membership in the more receptive profiles.

The profiles also provided nuanced insights into personality dimensions. For example, *Empty Promisers* exhibited higher extraversion but lower openness and conscientiousness compared to *Committed Realists*. These findings align with previous research that has suggested that conscientious students are more motivated to use feedback effectively, driven by their performance-oriented tendencies (Winstone et al., 2021). Similarly, openness, which is linked to intellectual curiosity (Komarraju et al., 2011; Meyer et al., 2023), was observed in the *Committed Realists*. By contrast, the extraversion seen in *Empty Promisers* may reflect a preference for social interaction over deep engagement with feedback (De Raad & Schouwenburg, 1996; Meyer et al., 2024; Poropat, 2009).

Finally, Study 3 highlighted key demographic findings. While gender did not significantly predict RIF profile membership, age-related differences were observed, as students in the *Empty Promisers* profile tended to be older than those in the *Indifferent Nonresponders* profile. This finding mirrors research findings in industrial and organizational settings, where age has been shown to influence feedback responses (Wang et al., 2014), which has now been demonstrated in educational contexts as well. Taken together, the findings illustrate the value of combining variable- and person-centered approaches to gain a comprehensive understanding of how individual characteristics and feedback receptivity interact across diverse educational contexts.

5.3 Research Question 2

RQ2: How does students' receptivity to instructional feedback relate to (a) performance and (b) interest?

The second central research question of this dissertation focused on the associations between students' RIF and two key educational outcomes: (a) revision performance and (b) triggered situational task interest. Both variable- and person-centered approaches were used to address this question, and ultimately provided complementary insights into how RIF dimensions and profiles relate to these outcomes.

Regarding revision performance, the findings demonstrated the nuanced role of different RIF dimensions. Study 2 showed that students who displayed higher behavioral engagement (acting on feedback) and stronger instrumental attitudes (valuing feedback as a tool for improvement) achieved better revision performance in an argumentative writing task. In contrast, general receptivity, cognitive engagement (strategies for processing feedback), and experiential attitudes (preferences for receiving feedback) were not significantly associated with improved

revision outcomes in this context. These findings suggest that while certain dimensions of RIF, such as behavioral engagement and instrumental attitudes, are linked to performance improvements, others may not directly contribute to specific task performance. This aligns with findings from Study 1 and prior research (e.g., Lipnevich & Lopera-Oquendo, 2022), which identified positive associations between RIF dimensions and broader measures of academic achievement, such as GPA. The modest effect sizes observed in Study 2 may accumulate over time, supporting the hypothesis that trait-like RIF exerts a more pronounced influence on cumulative outcomes than on specific, one-time tasks.

Triggered situational task interest was another key outcome examined. Study 2 found that general receptivity was positively associated with increases in task interest, whereas specific dimensions such as behavioral and cognitive engagement and attitudes toward feedback did not show significant associations. This suggests that general receptivity, reflecting students' overall competence in handling feedback, may enable students to process and utilize feedback more effectively, thus fostering greater interest in tasks (Renninger & Hidi, 2022). Students with higher general receptivity may possess a broader capacity to engage with feedback constructively, which could explain the unique role of general receptivity in enhancing triggered situational interest.

Study 3 provided additional insights into how RIF profiles are related to revision performance. Interestingly, behavioral engagement alone did not predict better outcomes. For example, students in the *Empty Promisers* profile, despite their low behavioral engagement, achieved similar revision outcomes to those in the *Committed Realists* profile, which exhibited high behavioral engagement. This highlights that behavioral engagement must interact with other factors, such as cognitive engagement and positive attitudes toward feedback, to effectively enhance performance. *Committed Realists*, characterized by a favorable combination of high behavioral and cognitive engagement and strong experiential and instrumental attitudes, demonstrated an optimal profile for utilizing feedback effectively. In contrast, *Empty Promisers*' low cognitive engagement, low general receptivity, and less positive attitudes toward feedback may have hindered their ability to capitalize on their behavioral tendencies. These findings align with prior research (e.g., Brown & Glover, 2006), emphasizing that feedback receptiveness is shaped by a multifaceted interplay of behavioral, cognitive, and affective factors.

The lack of performance differences between the *Empty Promisers* and *Committed Realists* profiles underscores the complexity of feedback utilization. Behavioral engagement alone is

insufficient; it must be accompanied by cognitive and affective components to translate into effective feedback use. For instance, while *Committed Realists* integrated high engagement across multiple dimensions, *Empty Promisers* lacked the cognitive and attitudinal foundations necessary to maximize the benefits of their feedback-related behaviors. These results further emphasize the importance of considering how behavioral, cognitive, and affective dimensions interact to shape feedback outcomes, illustrating the multifaceted nature of RIF.

5.4 Theoretical and Practical Implications

The field of feedback research has undergone a significant paradigm shift in recent years, moving away from viewing feedback as a universally effective instructional tool toward emphasizing the critical role of individual student characteristics in determining feedback effectiveness (Lipnevich & Smith, 2022; Panadero & Lipnevich, 2022). Contemporary feedback research increasingly highlights that the impact of feedback is shaped not only by the quality of the feedback itself but also by factors such as students' RIF, cognitive abilities, personality traits, perceptions of feedback, prior achievement, and demographic characteristics (Panadero & Lipnevich, 2022). This shift has led to the emergence of concepts such as *feedback literacy*, which captures the knowledge, skills, and attitudes necessary for students to effectively engage with feedback (Carless & Boud, 2018; Nieminen & Carless, 2022). Situated within this evolving paradigm, the present dissertation investigated students' RIF—a multidimensional, trait-like construct that reflects students' tendencies to accept and engage with feedback (Lipnevich & Lopera-Oquendo, 2022). The present dissertation highlights the need to prioritize students' *feedback literacy*, rather than focusing solely on feedback content, to more effectively address the relation between individual differences and feedback outcomes. To develop *feedback literacy*, students must first accept the feedback they receive.

Therefore, a core contribution of this dissertation is that it advances the validation of the RIF construct as an important prerequisite of students' *feedback literacy*. The findings derived from examining RQ1 highlight the multidimensional nature of RIF and its distinction from related constructs, such as personality traits. The dimensions of RIF—behavioral and cognitive engagement, as well as experiential and instrumental attitudes—are distinct and cannot be reduced to existing personality frameworks. For example, different RIF dimensions were associated with distinct patterns of personality traits, reinforcing the construct's unique theoretical standing. Moreover, students' membership in the three receptivity profiles—*Indifferent Nonresponders*, *Empty Promisers*, and *Committed Realists*—was predicted by distinct patterns of personality traits. This underscores that RIF is not merely a reflection of

broader individual characteristics but instead represents a targeted construct with unique implications for feedback engagement and learning outcomes. By clarifying these interrelations, this research contributes to a more nuanced theoretical understanding of RIF as a construct that encapsulates both general tendencies and profile-specific differences.

A particularly noteworthy finding is the presence of a general receptivity factor that extends beyond the technical aspects of the scale's validation. The identification of this factor has significant theoretical implications for understanding feedback receptivity. It suggests that RIF encompasses both specific dimensions and an overarching general tendency to engage with feedback. This discovery refines the theoretical conceptualization of RIF by positioning it as a construct that integrates both specific dimensions and a general orientation toward receiving feedback and is more in line with the initial conceptualization of receptivity as “a general, trait-like feedback receptivity” (Lipnevich & Lopera-Oquendo, 2022, p. 1).

Beyond construct validation, the findings from this dissertation contribute to a deeper understanding of how the student–feedback interaction is conceptualized. According to the process model of the student–feedback interaction (Lipnevich & Smith, 2022), this interaction is best understood as a dynamic loop in which the student engages with feedback within a specific context. The process begins with the feedback itself and the agent delivering it, and this is followed by the student's cognitive, affective, and behavioral processing of the feedback. The final phase involves the actions taken by the student and the resulting outcomes, such as improvements in performance or motivation. The findings obtained from examining RQ2 provide empirical support for this model. Specifically, students' RIF was associated with better performance and higher motivation; this underscores the importance of the interplay between individual student characteristics and the feedback message in shaping educational outcomes. These findings highlight the critical role of students' *feedback literacy*—their knowledge, skills, and attitudes toward engaging with feedback—over and above the content of the feedback itself. This evidence reinforces the theoretical understanding that the interaction between student characteristics and feedback is central to the effectiveness of feedback.

In examining the effects of feedback on motivation, particularly on interest, this dissertation followed the recommendations outlined in the four-phase model of interest development (Hidi & Renninger, 2006). This model posits that students have specific feedback needs and wants depending on their stage of interest development. Students need feedback that provides a limited number of concrete suggestions while also acknowledging their efforts, helping them to feel valued and supported. At the same time, students want feedback that not only tells them

what to do but also offers clear, actionable guidance on how to do it. Moreover, they want their ideas to be seen and respected. Feedback that aligns with these needs and wants has the potential to spark and sustain their triggered situational interest (Renninger & Hidi, 2022). Indeed, adhering to these recommendations and providing feedback that aligned with students' needs and wants proved to be beneficial in this dissertation. Students who exhibited high general receptivity to feedback experienced greater triggered situational interest; this finding supported the recommendations of the four-phase model (Renninger & Hidi, 2022). Furthermore, students' perceptions of feedback usefulness emerged as a key factor, as it may reflect students' ability to recognize concrete suggestions for improvement (Renninger & Hidi, 2022). This finding is supported by the strong association between perceived feedback usefulness and task interest observed in this and other studies (Harks et al., 2014; Rakoczy et al., 2013, 2019). These results suggest that students' perceptions of feedback usefulness may serve as a meaningful indicator of whether feedback successfully meets their needs and that positive perceptions of feedback usefulness can foster greater engagement and interest in the task.

A practical implication of this dissertation is that researchers and practitioners in German-speaking regions can now utilize the translated and adapted RIF scale in computer-based assessment settings. With an average completion time of under three minutes, the scale is both practical and efficient for large-scale applications.

In addition, findings from this dissertation lay the groundwork for designing targeted feedback interventions that align with the specific needs of students in their individual RIF profiles, ultimately enhancing the effectiveness of such interventions in educational settings. For example, *Indifferent Nonresponders* may benefit from explicit scaffolds designed to cultivate a more positive attitude toward feedback, such as process-oriented feedback, which has been shown to improve perceptions of usefulness compared to outcome-oriented feedback (Harks et al., 2014). *Empty Promisers*, who exhibit an initial willingness to act on feedback but struggle with follow-through, might respond well to structured, step-by-step revision guidance that supports them in translating intent into action (Sadler, 2010). In contrast, *Committed Realists* could thrive with agentic feedback that challenges their abilities and fosters further growth, rather than merely offering encouragement (Griffiths et al., 2023). By aligning feedback strategies with students' receptivity profiles, instructional support can become more precise and impactful, particularly in digital learning environments where personalized feedback has significant potential to optimize educational outcomes.

Furthermore, the RIF scale could serve as a valuable tool for identifying students who may be at risk of disengaging from feedback processes. By assessing students' receptivity profiles early on, educators and institutions could proactively implement tailored interventions to support those less inclined to act on feedback. Designing reappraisal interventions that specifically address the needs of each profile could further enhance receptivity and engagement. For instance, fostering a growth-oriented mindset in *Indifferent Nonresponders*, strengthening commitment strategies for *Empty Promisers*, or providing challenge-based scaffolding for *Committed Realists* may help students develop more adaptive feedback engagement patterns. Integrating such targeted interventions into instructional design could enhance the long-term impact of feedback and contribute to more effective learning experiences.

5.5 Limitations

Several limitations should be considered when interpreting the findings of this dissertation. One aim of this dissertation was to investigate the associations between students' trait-like RIF dimensions and their performance and motivational outcomes. To this end, across all three studies, the RIF scale was administered only once at the start of the interventions. Consequently, this approach did not allow us to determine whether RIF itself may be influenced by the feedback provided during the interventions. Furthermore, the studies focused on a single feedback instance, limiting the ability to examine RIF's influence across multiple feedback situations. Longitudinal research is needed to assess the stability of the identified RIF profiles over time and explore the extent to which RIF is a truly stable, trait-like construct versus one influenced by situational and contextual factors.

Studies 2 and 3 in this dissertation were conducted within the context of automated computer-based feedback on authentic argumentative writing tasks. Although this approach ensured high ecological validity by examining feedback in real-world classroom settings, it introduced certain limitations. First, environment-related variables could not be fully controlled, which may have influenced the findings. Although randomization at the student level and relatively large sample sizes helped mitigate the impact of confounding variables, the complexity of real-world classrooms inherently limits the control over extraneous factors. For instance, Study 3 highlighted that socio-cultural factors—such as the quality of the relationship with the feedback provider—were not accounted for, even though these factors are known to significantly influence feedback engagement (Luo, 2023; Sargeant et al., 2010). Second, although these studies were conducted in real-world classroom settings, they took place in low-stakes learning environments where students were aware that their performance would not be observed by a

teacher or impact their grades. As a result, the findings may not be generalizable to high-stakes contexts.

Another limitation of this research is that it only examined computer-based feedback. While automated computer-based feedback offers consistency and scalability, it differs significantly from human-delivered feedback, which may include relational dynamics, a specific tone, and different nuances (Fong & Schallert, 2023). Consequently, the findings may not fully generalize to traditional classroom settings where teacher-delivered feedback is more common. Additionally, this dissertation focused exclusively on argumentative writing tasks. Although RIF is conceptualized as a trait-like tendency to accept feedback across domains (Lipnevich et al., 2021; Lipnevich & Lopera-Oquendo, 2022), there may be domain-specific variations in feedback receptivity. For example, students might respond differently to feedback in subjects they find particularly engaging or challenging. Feedback in tasks requiring different skills (e.g., mathematical problem-solving) may elicit different responses, depending on students' domain-specific attitudes, prior knowledge, and competencies. Future studies should examine RIF across a broader range of task types to better determine its domain-specific and task-specific manifestations.

This dissertation relied on self-reported measures of RIF and perceptions of feedback usefulness. A major obstacle to measuring the influence of students' dispositions and perceptions on feedback effectiveness is that it requires self-reports from the learners themselves, in addition to objective performance measures (Brown & Zhao, 2023). However, relying on self-report data has well-known limitations (for a systematic review of contemporary self-report feedback inventories, see Brown & Zhao, 2023) and, although it is a key objective of psychological science, "almost no high-quality research has been done in education that links perceptions of feedback to subsequent behaviors" (Brown & Zhao, 2023, p. 188). To advance the field, it is crucial to apply strong psychometric methods and systematically link self-reports to observable outcomes. Future studies could strengthen the validity of findings by incorporating objective measures, such as behavioral indicators of feedback engagement (see Schiller et al., 2024).

The investigation of feedback's effects on interest in this dissertation focused on triggered situational interest, which is the initial phase of interest development described in the four-phase model (Hidi & Renninger, 2006). As such, the findings are limited to this early phase and do not address subsequent phases, such as the phases of maintained situational interest or

emerging individual interest. Further research is needed to determine whether the effects of RIF on interest extend to the later phases of the model.

Finally, the participants in the studies of this dissertation were students in German-speaking learning environments. As such, the findings may not fully generalize to other cultural, linguistic, or educational contexts. Feedback receptivity is probably influenced by cultural norms and practices, which may shape how students perceive and engage with feedback (Lipnevich & Lopera-Oquendo, 2022). Cross-cultural research could provide valuable insights into the broader applicability of the RIF construct. This work is already underway, including cross-cultural research on the broader applicability of the RIF construct, as well as the development and validation of a short scale for its assessment.

5.6 Future Directions

The aim of this dissertation was to elucidate why some students benefit more from feedback than others. Within the new paradigm of feedback research, the central idea is that feedback cannot be assumed to influence learning unless students actively engage with it (Henderson et al., 2019). Effective engagement requires *feedback literacy*, but the development of *feedback literacy* presupposes an initial willingness to accept feedback. Consequently, individual differences in students' RIF emerged as a promising lens through which the overarching question of this dissertation could be addressed.

Nonetheless, this dissertation represents only one piece of a larger puzzle and should not be considered in isolation from other critical factors identified in the literature, such as the other dimensions of the MISCA model (e.g., Message, Implementation, Student, Context, and Agents; Panadero & Lipnevich, 2022). Fully understanding why some students benefit more from feedback than others requires an integrative approach that considers these interconnected factors.

This dissertation highlights several avenues for future research. First, while this work treated RIF as a relatively stable, trait-like construct, it remains unclear whether RIF can also be influenced by the feedback provided during interventions. Investigating this dynamic interplay would offer valuable insights into whether RIF is a fixed characteristic or one that can be changed through targeted feedback practices. Additionally, longitudinal studies are needed to explore the stability of RIF across multiple feedback situations and its cumulative effects on performance and motivation over time.

A broader integration of psychological and socio-cultural perspectives is also essential to fully understand feedback receptivity. For instance, factors such as the quality of the feedback-provider relationship and the context in which feedback is delivered may mediate or moderate the impact of RIF on educational outcomes. Future research should examine how relational dynamics, socio-cultural factors, and contextual variables interact with students' RIF, as the results of such research could provide a more holistic understanding of the feedback process.

To enhance the generalizability of findings, further research should explore students' RIF in a variety of educational domains beyond argumentative writing. Different academic tasks, such as problem-solving tasks in mathematics, may reveal domain-specific differences in feedback receptivity. Similarly, the quality of feedback is an important avenue for exploration. Although the feedback messages used in this dissertation were carefully designed to provide valuable information, their impact on students' revision performance was limited. Future studies should investigate whether students with different RIF profiles respond differently to feedback of varying quality, from low-quality or incorrect feedback (e.g., AI-generated feedback) to high-quality, personalized feedback provided by teachers. As AI-generated feedback becomes increasingly common, it is especially important to understand how its characteristics and reliability affect student engagement and outcomes. Also, it would be interesting to explore whether students may have a different receptiveness to computer-based feedback that is explicitly flagged as having been generated by AI.

Future research should also validate the findings of this dissertation in contexts involving human-delivered feedback, particularly in German-speaking classrooms. As feedback effects can be context-dependent (Fong & Schallert, 2023), further studies should examine how RIF manifests in traditional classroom settings with human feedback providers compared to digital environments. Exploring differences in receptivity across feedback agents, such as teachers, peers, and automated systems, could yield valuable insights (Panadero & Lipnevich, 2022).

Additionally, process data could deepen the understanding of how behavioral engagement influences revision performance. For example, Schiller et al. (2024) demonstrated that behavioral engagement—measured through metrics such as revision time and edit distance—mediated the positive effects of feedback on revision outcomes. Future research could incorporate such log-data alongside self-reported measures of behavioral engagement to provide a more comprehensive view of feedback effectiveness.

Another area for future inquiry is the role of affective reactions to feedback. Measuring students' emotional responses to feedback, either as an outcome (see Panadero & Lipnevich,

2022) or as a moderator of RIF, could provide additional insights. Negative emotional reactions, such as discomfort or frustration, may influence students' willingness to accept feedback, potentially moderating the relationship between RIF and feedback engagement. An improved understanding of these affective dynamics could be beneficial in the design of interventions that minimize negative reactions while fostering constructive feedback engagement.

In summary, future research should adopt a multidimensional approach, combining psychological, socio-cultural, and contextual perspectives to deepen the understanding of RIF and its role in feedback processes. By exploring these avenues, researchers can further unravel why some students benefit more from feedback than others, thereby paving the way for more effective, personalized feedback interventions in diverse educational settings.

5.7 General Conclusion

This dissertation set out to answer a critical question in contemporary feedback research: Why do some students benefit more from feedback than others? Situated within the emerging paradigm that emphasizes the importance of individual differences in feedback engagement and effectiveness, this work has shed light on students' RIF as a key construct in understanding this variability (Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Wisniewski et al., 2020).

At its core, this research highlights that feedback is not inherently effective—it must be actively engaged with by students to translate into meaningful learning outcomes. The findings underscore the importance of RIF as a prerequisite for *feedback literacy*, which—in turn—is necessary for effective feedback engagement. Through the validation of the RIF construct and the identification of distinct RIF profiles—*Indifferent Nonresponders*, *Empty Promisers*, and *Committed Realists*—this dissertation has shown that feedback receptivity is multidimensional and shaped by cognitive ability, personality traits, and age, as identified in the guiding MISCA model (Panadero & Lipnevich, 2022). These profiles illustrate that students differ not only in their willingness to accept feedback but also in how they process and act upon it, ultimately influencing their performance and motivation.

The studies within this dissertation provide empirical evidence for the nuanced role that RIF dimensions play in shaping educational outcomes. Behavioral engagement and instrumental attitudes, for instance, were found to be particularly influential in improving revision performance, while other dimensions, such as general receptivity and cognitive engagement, may exert more subtle or long-term effects. These findings contribute to a growing body of

literature that positions feedback not as a one-size-fits-all tool but as a process that must be tailored to the unique needs and characteristics of individual learners (Fleckenstein et al., 2023).

In addition to advancing the theoretical understanding of feedback processes, this dissertation also emphasizes the need for practical innovations in feedback delivery. The validated German-language RIF scale offers researchers and practitioners a reliable and valid tool for assessing feedback receptivity within computer-based environments. Moreover, the findings provide actionable insights that can be used to design feedback interventions that align with students' RIF profiles, thereby enhancing the effectiveness of feedback interventions. For example, explicit scaffolds may help *Indifferent Nonresponders* develop more positive attitudes toward feedback, while structured revision guidance may support *Empty Promisers* in translating intent into action. Meanwhile, *Committed Realists* are likely to benefit most from feedback that challenges and extends their abilities.

Despite these contributions, this dissertation acknowledges that feedback receptivity is only one piece of the puzzle in understanding why some students benefit more from feedback than others. The interplay between RIF and other factors of the MISCA model (e.g., Message, Implementation, Student, Context, and Agents) remains an important area for future exploration (Panadero & Lipnevich, 2022). Furthermore, the findings from this dissertation, while promising, are limited to computer-based feedback in the domain of argumentative writing and, thus, further research is necessary to generalize and expand upon these results.

In conclusion, this dissertation aligns with the new paradigm of feedback research, which emphasizes the importance of individual differences in addition to feedback content in understanding feedback effectiveness. Through the validation of the RIF construct, this work provides a valuable framework for explaining part of the variability in feedback effectiveness. Ultimately, it highlights that the effectiveness of feedback depends not only on its content or delivery but fundamentally on the student receiving it. By identifying RIF as a key factor, this dissertation underscores its potential as a foundation for developing *feedback literacy*, which empowers students to engage with and make meaningful use of computer-based feedback, ensuring its impact on learning.

5.8 References

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Chapter 6 – Appendices

6.1 German Summary – Deutschsprachige Zusammenfassung

Feedback spielt eine zentrale Rolle in modernen Lehrpraktiken und ist ein wesentliches Instrument zur Förderung des Lernens in verschiedenen Bildungskontexten (Panadero & Lipnevich, 2022). Fortschritte in der Bildungstechnologie haben die Bereitstellung personalisierten Feedbacks erleichtert und tragen zur Förderung von Chancengleichheit im Bildungsbereich bei (Mertens et al., 2022). Dies ist insbesondere angesichts des Lehrkräftemangels (z. B. Jensen, 2021) und der zunehmenden Verbreitung von Online-Bildung von Bedeutung, da automatisiertes Feedback skalierbare Lösungen bietet. Obwohl das Potenzial von Feedback zur Verbesserung von Lernleistungen gut belegt ist (z. B. Camacho et al., 2021; Graham et al., 2015, 2023, 2024), bleibt seine Wirksamkeit uneinheitlich und variiert zwischen einzelnen Lernenden (Wisniewski et al., 2020). Trotz jahrzehntelanger Forschung zur Wirkung von Feedback auf Lernprozesse (Bangert-Drowns et al., 1991; Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Kulhavy, 1977; siehe Lipnevich & Panadero, 2021 für eine historische Übersicht) bleibt unklar, warum einige Lernende stärker davon profitieren als andere (Winstone & Nash, 2023).

Um diesen individuellen Unterschieden Rechnung zu tragen, hat sich die Feedbackforschung zunehmend auf spezifische Merkmale der Lernenden konzentriert, darunter Rezeptivität für Feedback, Feedbackwahrnehmungen, kognitive Fähigkeiten, Persönlichkeitsmerkmale, Vorwissen, Alter und Geschlecht (Panadero & Lipnevich, 2022). Ein zentrales Prinzip dieses Paradigmas ist, dass Feedback nur dann Lernen beeinflusst, wenn es aktiv verarbeitet wird (Henderson et al., 2019). Ein wesentliches Problem besteht jedoch darin, dass viele Lernende trotz erhaltenen Feedbacks keine Leistungssteigerung erzielen, da sie es nicht aktiv verarbeiten (Mensink & King, 2020; Winstone et al., 2021; Wu & Schunn, 2020).

Die Variabilität in der Wirksamkeit von Feedback zeigt, dass es keine universelle Lösung darstellt (Fleckenstein et al., 2023). Damit Lernende Feedback sinnvoll nutzen können, benötigen sie Wissen, Fähigkeiten, Einstellungen und Dispositionen zur Interpretation und Anwendung – zusammengefasst als *Feedback Literacy* (Carless & Boud, 2018; Dawson et al., 2023; Molloy et al., 2020; Nieminen & Carless, 2022). Entscheidend hierfür ist die Bereitschaft, Feedback anzunehmen, die durch das Konstrukt der Rezeptivität für instruktionales Feedback (RIF) nach Lipnevich et al. (2021) operationalisiert wird. RIF beschreibt ein mehrdimensionales Konzept, das behaviorales und kognitives Engagement mit Feedback sowie instrumentelle und affektive Einstellungen umfasst.

RIF könnte eine entscheidende Voraussetzung für die Entwicklung von *Feedback Literacy* und die Wirksamkeit von Feedback sein. Aufgrund der Neuheit des Konstrukts sind seine Zusammenhänge mit Faktoren, die die Verarbeitung und Nutzung von Feedback beeinflussen, bislang kaum erforscht. Ebenso fehlt es an Evidenz zur Verbindung zwischen RIF, Leistung und Motivation in realen Lernkontexten (Lipnevich & Lopera-Oquendo, 2022). Diese Dissertation untersucht daher die Frage: Warum profitieren manche Lernende stärker von Feedback als andere? Konkret adressiert die Arbeit zwei zentrale Forschungsfragen:

1. Wie hängt die RIF der Lernenden mit anderen individuellen Merkmalen zusammen, die für die Verarbeitung und Nutzung von Feedback relevant sind?
2. Wie hängt die RIF der Lernenden mit (a) Leistung und (b) Interesse zusammen?

Drei empirische Studien untersuchten diese Fragen in einer digitalen Lernumgebung mit automatisiertem computerbasiertem Feedback zur Förderung argumentativer Schreibkompetenzen. Studie 1 legte die Grundlage für die weiteren Untersuchungen, indem eine angepasste und übersetzte Version der RIF-Skala für den Einsatz in computerbasierten Assessments im deutschsprachigen Raum validiert wurde. Da psychometrische Eigenschaften adaptierter Instrumente von den Originalversionen abweichen können (Gudmundsson, 2009), ist eine sorgfältige Validierung essenziell (Beaton et al., 2000; Hofverberg & Winberg, 2020; Leitgöb et al., 2022). Anhand von Daten deutscher Studierender ($N = 464$; $M_{Alter} = 24,3$, $SD = 4,4$) sowie Schülerinnen und Schüler ($N = 1207$; $M_{Alter} = 16,0$, $SD = 1,4$) zeigte das bifaktorielle CFA-Modell eine gute Passung, wobei neben einem generellen Rezeptivitätsfaktor vier spezifische Faktoren identifiziert wurden: affektive und instrumentelle Einstellungen, und kognitives und behaviorales Engagement. Die skalare Messinvarianz ermöglichte Vergleiche über Geschlecht und Bildungsniveaus hinweg. Die konvergente Validität wurde durch positive Zusammenhänge mit Schulnotendurchschnitt gestützt, während differenzielle Assoziationen mit Persönlichkeitsmerkmalen die diskriminante Validität bestätigten. Damit beantwortete Studie 1 die erste Forschungsfrage, indem sie den Zusammenhang zwischen RIF und relevanten individuellen Merkmalen untersuchte und zugleich die Reliabilität der adaptierten RIF-Skala bestätigte.

Studie 2 adressierte primär die zweite Forschungsfrage, indem sie den Einfluss des allgemeinen sowie der vier spezifischen RIF-Dimensionen auf die Überarbeitungsleistung und das Aufgabeninteresse untersuchte – mit besonderem Fokus auf die vermittelnde Rolle der wahrgenommenen Feedback-Nützlichkeit. Die Stichprobe umfasste 1507 deutsche Schülerinnen und Schüler ($M_{Alter} = 16,4$, $SD = 1,4$), die in einer Unterrichtssituation einen

argumentativen Text schrieben, automatisiertes Feedback erhielten und ihre Texte überarbeiteten. Strukturgleichungsmodelle zeigten, dass insbesondere behaviorales Engagement und instrumentelle Einstellungen für die Verbesserung der Überarbeitungsleistung entscheidend waren. Zudem vermittelte die wahrgenommene Nützlichkeit des Feedbacks den Zusammenhang zwischen genereller Rezeptivität und steigendem Aufgabeninteresse. Neben der Klärung von Zusammenhängen zwischen RIF-Dimensionen und lernrelevanten Ergebnissen trug diese Studie auch zur ersten Forschungsfrage bei, indem sie das Zusammenspiel von stabilen und situativen individuellen Unterschieden bei der Feedbackverarbeitung beleuchtete und damit die Diskussion um *Feedback Literacy* erweiterte.

Studie 3, die primär die erste Forschungsfrage untersuchte, umfasste eine große Stichprobe von deutschen Schülerinnen und Schülern ($N = 1,800$; $M_{Alter} = 16,37$, $SD = 1,47$), die eine argumentative Schreibaufgabe bearbeiteten, automatisiertes Feedback erhielten und ihren Text überarbeiteten. Ziel war es, eine umfassende Beschreibung von RIF-Profilen zu liefern, indem (1) unterschiedliche Profile identifiziert und charakterisiert, (2) Unterschiede in der Profiltugehörigkeit basierend auf kognitiven Fähigkeiten, Persönlichkeitsmerkmalen, Vorwissen, Alter und Geschlecht analysiert und (3) Zusammenhänge zwischen RIF-Profilen und Überarbeitungsleistung untersucht wurden. Eine latente Profilanalyse identifizierte drei unterschiedliche Profile, die sich in ihrem Ausmaß an behavioralem und kognitivem Engagement, affektiven und instrumentellen Einstellungen sowie genereller Rezeptivität unterschieden: *Indifferent Nonresponders*, *Empty Promisers* und *Committed Realists*. Das leistungsschwächste Profil, die *Indifferent Nonresponders*, war durch geringere kognitive Fähigkeiten, eine niedrigere Verträglichkeit und höhere Neurotizismus-Werte gekennzeichnet. Hinsichtlich der Überarbeitungsleistung zeigten sich keine Unterschiede zwischen *Empty Promisers* (geringes behaviorales Engagement) und *Committed Realists* (hohes behaviorales Engagement), was darauf hindeutet, dass behaviorales Engagement allein nicht ausreicht, sondern mit weiteren RIF-Faktoren interagiert.

Zusammenfassend greift diese Dissertation die in der Feedbackforschung zunehmende Fokussierung auf individuelle Unterschiede auf (Panadero & Lipnevich, 2022). Durch die Validierung des RIF-Konstrukts bietet sie einen Ansatz zur Erklärung der Variabilität in der Feedbackwirksamkeit und betont, dass deren Wirkung maßgeblich von den Lernenden abhängt. Die Identifikation von RIF als zentralem Faktor unterstreicht dessen Potenzial zur Förderung von *Feedback Literacy* und zur Entwicklung effektiver, skalierbarer technologiegestützter Feedbackprozesse.

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