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Implicit Intelligence Mindset, Behaviour after Failure and the Role of Controllability Attribution

Failure in one form or another is part of every student's academic experience. However, it is not necessarily the failures that students experience, but rather the way in which they react to these setbacks that has a significant impact on a student's academic success. It's important to understand why some students become demotivated and suffer from negative repercussions while others bounce back from failure experiences and might even thrive from them.

Past research has shown that the beliefs that students hold about the malleability of their intelligence play an important role when it comes to coping with experiences of failure in an academic context. Dweck (2006) proposed that students might either view their intelligence as something fixed and unchangeable (fixed mindset) or they might view it as something that can be developed and improved (growth mindset). These beliefs have shown to be related to students' academic success (Blackwell et al., 2007), self-esteem (Gál et al., 2020) and wellbeing (Alvarado et al., 2019).

Because of the observed influence of these beliefs on students' academic success and wellbeing, different interventions haven been designed and implemented to change these beliefs and foster a growth mindset in an educational setting. There is growing body of data on the effectiveness of these mindset interventions, such as a recent large-scale study by Yeager et al. (2019), showing their positive influence on academic success such as student grades. Although the effects of growth mindset on holistic learning outcomes such as grades have been thoroughly investigated, the direct behavioural consequences of pre-existing mindsets in response to academic setbacks (e.g. persistence on a difficult task or adapting learning behaviour) have gotten little attention so far. An early study examining students' behavioural responses to setbacks found that those who endorse a growth mindset were more likely to take remedial action following a failure experience (Hong et al., 1999). A better understanding of immediate behavioural responses may help to bridge the gap between students' mindsets and more holistic outcomes such as their academic success.

When studying students' responses to setback, it's also interesting to look at how they interpret the reasons for their failure. Attribution has been considered an important factor in explaining the adaptive influence of a growth mindset following a setback (Diener & Dweck, 1978; Dweck, 1975, Dweck & Reppucci, 1973; Hong et al., 1999). In a recent study, controllability attribution has been shown to play a role in this relationship (Song et al., 2020).

Additionally, with the increasing presence of growth mindset in media and educational contexts, it may have become more socially desirable for individuals to endorse such beliefs. Adding to the heterogeneous findings on the topic, with two recent meta-analyses showing little to no effect of mindset on academic achievement (Costa & Faria, 2018; Sisk et al., 2018), the need for different measures of students' intelligence mindset becomes apparent. Although implicit measures are more highly correlated with behaviour than explicit measures when dealing with socially sensitive constructs (Forscher et al., 2019), there has been little research assessing intelligence mindset using such an implicit measure.

Thus, the purpose of this thesis is to investigate the relationship between students' mindset and their behavioural responses following a supposed failure experience as well as looking at the role of controllability attribution in this context. Participants' intelligence mindset will be implicitly assessed, in addition to assessing it explicitly with a questionnaire to potentially offer new perspectives on intelligence mindsets that might not be captured by self-report measures.

Intelligence Mindset and Failure

Before looking at the relationship between intelligence mindset and student's responses to setbacks, the construct of intelligence mindset will be explained in more detail. Implicit theories such as intelligence mindset play a role in shaping the frameworks and meaning systems used by people to make sense of their experiences (Yeager & Dweck, 2012) and can lead to different motivational and performance outcomes (Hong et al., 1999). Mindset theory postulates, that individuals can be characterised by their beliefs about their personal traits such as intellectual abilities.

They might differ in how malleable or fixed they view these traits. On the one hand, individuals may hold what is known as a growth mindset or incremental beliefs. This is characterised by the belief, that intellectual abilities can be changed and developed. Individuals with a fixed mindset or entity beliefs on the other hand believe that these abilities are fixed and unchangeable (Dweck, 1999; Dweck & Leggett, 1988). Facets of both mindsets may be present simultaneously (Burnette et al., 2013), depending on situational factors such as the respective academic domain (Quihuis et al., 2002). Different mindsets might lead to different goals and behaviours in an educational setting and therefore might play an important role in a student's overall academic success. Students endorsing a fixed intelligence mindset may aim to prove that their level of intelligence is high. They tend to adopt performance goals such as achieving good grades to demonstrate their abilities rather than aiming to improve them (Cury et al., 2006; Dweck & Leggett, 1988). Subsequently, they tend to avoid challenges and may give up when faced with academic obstacles for fear of revealing insufficient intelligence (Henry et al., 2019; Paunesku et al. 2015). For these students, struggles or failures imply a lack of ability leading to helpless strategies such as giving up or withdrawing, and may elicit negative affective reactions (Burnette et al., 2013; Dweck & Leggett, 1988). Thus, fixed mindset has been shown to predict lower achievement in the face of academic challenges or failure experiences (Blackwell et al., 2007).

Students endorsing a growth mindset, on the other hand, aim to learn and grow their intellectual abilities (Dweck, 1999). They tend to adopt mastery goals and focus on improving their abilities rather than proving them (Cury et al., 2006; Dweck & Leggett, 1988). Consequently, they are more likely to seek out challenging tasks to grow from them (Henry et al., 2019). Furthermore, they view failure as a lack of effort rather than a lack of ability and demonstrate positive learning strategies and persistence (Blackwell et al., 2007; Burnette et al., 2013). Through the adoption of a mastery goal and effort attributions, a growth mindset about intelligence and academic ability can act as a buffer against a potentially demotivating situation such as an academic setback (Aditomo, 2015) and have a positive influence on more general learning outcomes e.g. academic grades (Yeager & Dweck, 2020).

While there has been extensive research on the effectiveness of mindset interventions as well as their influence on motivation and academic success, only little research has looked at direct behavioural responses to a failure experience (see Dweck & Yeager, 2019). Looking at students' direct behavioural reactions to an academic setback might help to get a deeper understanding on how intelligence mindset influences broader learning outcomes. One of the few studies looking at direct behavioural responses to a failure experience in an academic setting, Hong et al. (1999) showed that students endorsing a growth mindset are more likely to take remedial actions. After receiving negative feedback on an intelligence test, students in the fixed mindset condition were less likely to choose to work on tutorial exercises for the following intelligence test and less likely to attribute their failure to a lack of effort compared to the students in the growth mindset condition. Another study involving engineering students (Nussbaum, & Dweck, 2008) showed similar results. Following negative feedback on a difficult spatial-reasoning exercise, students were asked to choose between taking a tutorial and a second test for a module of the test in which they previously performed well or taking a tutorial and repeating the test for the module they previously failed. Over 90 percent of the students in the growth mindset condition chose to do the tutorial for the module they needed help with compared to just over half of the students in the fixed mindset condition. Comparable results emerged when looking at the relationship between growth mindset and behavioural self-handicapping. Self-handicapping refers to the deliberate creation of obstacles or the act of self-sabotage to establish a preemptive excuse for potential failure, allowing the individual to attribute the failure to the handicap rather than a lack of ability (Berglas & Jones, 1978; Rhodewalt, 1994). After experiencing a setback, students who had been exposed to a fixed mindset message about giftedness engaged in more behavioural self-handicapping than those who had been listening to a growth mindset message about giftedness (Snyder et al., 2014). Similarly, students primed with a fixed mindset practiced less items for a verbal abilities test after doing the sample items compared to students primed with a growth mindset (Niiya et al., 2010).

In recent years, neuroscience studies have opened a new perspective on the effects of mindsets as well as given insight into the underlying neural mechanisms which might help explain behavioural outcomes. Individuals holding a fixed mindset show a stronger alerting response to failure feedback (Mangels et al., 2006) and a reduced attentional allocation to post-error adjustments (Moser et al., 2011; Schroder et al., 2017). Individuals endorsing a growth mindset conversely have greater coactivation at rest between learning related regions (e.g. the striatum) and other executive function regions (Myers et al., 2016), likely in order to support their flexible learning capacity. A study by Bejjani et al. (2019) showed that participants experiencing failure feedback on an IQ test had the strongest predictive relationships between mindset, performance, and caudate activation. The failure feedback may have intensified the subjective punishment of negative feedback for participants holding a fixed mindset relative to those holding a growth mindset, resulting in poorer learning from negative feedback.

Controllability Attribution

Different cognitive and motivational processes might be at play in the translation from mindset to behaviour. To explain the adaptive influence of growth mindset when facing a setback, students' attributions can be an important factor (Diener & Dweck, 1978; Dweck, 1975; Dweck & Reppucci, 1973; Hong et al., 1999). Attribution theory proposes that students' responses to a failure are shaped by three differing causal dimensions: locus, stability, and controllability (Weiner, 2010). Locus describes whether a cause is attributed to something inside or outside the student. Stability describes whether the cause is perceived as something stable over time or variable and last, controllability describes the degree to which a cause is perceived as something the student has control over or not. After attributing an outcome to the different causal dimensions, other emotions and future achievement strivings arise as psychological and behavioural consequences of the attribution process (Weiner, 1986). A recent study implementing meta-analytic structural equation modelling highlights the role controllability attribution plays in achievement contexts. A direct relationship between controllability attribution and behavioural adjustment emerged, which included

participants' intentions to act and the self-regulation strategies they plan to implement, as well as between controllability attribution and performance (Brun et al., 2021).

In the aforementioned study by Hong et al. (1999) students endorsing a fixed mindset attributed their performance more to ability than to effort following a failure experience. In contrast, the growth mindset group showed weaker ability and stronger effort attribution compared to the fixed mindset group. Intriguingly, when only looking at the growth mindset group, students attributed their failure as much to their effort as to their ability. Consequently, students endorsing a growth mindset might not view their ability as something fixed, but rather as something that is in their control to be changed. Therefore, growth mindset might amplify the perception of controllability of a cause of failure. The results from a more recent study are in line with this reasoning, showing controllability attribution as a mediator for the relationship between growth mindset and mastery goal adoption following a setback (Song et al., 2020).

Implicitness of Intelligence Mindset

Implicit theories such as intelligence mindset have been called "implicit" because they are believed to often be outside of the awareness of a person (Dweck & Yeager, 2019). Contrary to the proposed implicit nature of intelligence mindset in the above presented literature it has mainly been assessed using self-report measures (Dweck, 1999), which demand deliberate judgment in a questionnaire. This creates a mismatch between the proposed nature of intelligence mindset as unaware and the measures used to assess the construct.

Additionally, growth mindset has become more and more prominent in mainstream media and several influential companies such as Microsoft have adopted it into their corporate culture (Dweck & Hogan, 2016). Through mindset theory becoming more established outside the scientific community it might have become socially desirable to endorse a growth mindset. This should also be considered, when assessing it with self-report measures such as an explicit questionnaire (e.g. the Implicit Theories of Intelligence Scale (ITIS, developed by Dweck (1999))). Moreover, there might be introspective limits concerning one's own mindset and people might not even know what kind of intelligence mindset they endorse. Irrespective of their own beliefs, people might

agree with growth mindset items because they are familiar with the concept and the proposed advantages of endorsing such a mindset. The pressure to demonstrate attributes like a growth mindset can result in people merely echoing growth mindset ideas on the surface, aiming to boost self-reported progress rather than truly embodying profound shifts in their mindset (Duckworth & Yeager, 2015). Especially in the educational context a so called “false growth mindset” amongst teachers could be observed. (Dweck, 2015, 2016; Patrick & Joshi, 2019). This might manifest in misapplying the concept of growth mindset, for example in praising effort over progress or blaming mindset for students struggles instead of refocusing it. Endorsing growth mindset on a surface level and actually holding a growth mindset can therefore be challenging to distinguish using the common self-report measures. Subsequently, there is a need for other (implicit) measures to assess implicit theories such as growth mindset (Lüftenegger & Chen, 2017).

Forscher et al. (2019) showed that for socially sensitive topics implicit measures are correlated higher with behaviour than explicit measures, but so far there has been only little research using implicit measures to assess intelligence mindset. Mascaret and Cury (2015) for example found a difference between men and women concerning their theories of science intelligences, which only showed using an implicit association test (IAT, Greenwald et al., 1998) and not using a self-report measure.

Implicit Measures

Implicit measures intend to assess psychological attributes such as beliefs, attitudes, stereotypes etc without relying on self-reports from participants (Gawronski & De Houwer, 2014). They usually involve indirect tasks that measure the association strength between different stimuli such as words or images and the reaction time or accuracy of the participants' responses (Gawronski & De Houwer, 2014). One of the most well-known implicit measures is probably the Implicit Association Test (IAT; Greenwald et al., 1998), which aims to assess the strength of the association between a target concept (for example race or gender) and an attribute dimension (e.g. good - bad) in terms of reaction time latency (Fazio and Olson, 2003). More recent advancements in

implicit measurement of beliefs and attitudes broaden the focus not only on the question if stimuli are related but also on how they are related.

MT-PEP

A promising more recent approach is the so-called Propositional Evaluation Paradigm (PEP; Müller & Rothermund, 2019). The PEP uses the (mis)match between the sentences (propositions) shown and the responses demanded (e.g., responding “false” to a sentence that the participant believes to be true) to measure participants’ beliefs. It is intended to assess multiple beliefs in a single experimental block and therefore increases efficiency compared to other implicit measures. The PEP includes *probe* and *catch* trails. In a probe trail, participants are asked to respond to a “TRUE” or “FALSE” prompt, after having been shown a proposition in a word-by-word manner. They are instructed to react according to the prompt and irrespective of the meaning of the shown proposition. Longer response times are considered as a mismatch between the prompt and participants’ agreement or disagreement with the shown proposition (e.g. having to respond to “FALSE” although one agrees with the previously shown proposition). In a catch trail (implemented to ensure genuine engagement with the shown propositions), participants are presented with a “??TRUE OR FALSE??” prompt. Now they have to respond according to the spelling of the sentence shown beforehand by selecting either “true” (spelled correctly) or “false” (spelled incorrectly). Because the catch trails appear randomly throughout the PEP task and the prompt “??TRUE OR FALSE??” only shows after a proposition is presented, participants have to read every proposition thoroughly and therefore process their meaning to a certain degree.

In contrast to measuring response time, the mouse tracking version of the PEP (MT-PEP; Cummins & De Houwer, 2021; Müller & Rothermund, 2019) used in this thesis offers the possibility to observe how a participant’s response unfolds across a trial (Freeman, 2018; Hehman et al., 2015). Compared to the standard PEP it delivered larger effects, showed superior predictive validity, and better split-half reliability (Cummins & De Houwer, 2021). Furthermore, the MT-PEP has shown promising results in other areas such as beliefs about immigrants. The MT-PEP may be considered

implicit in the sense of capturing fast and unaware (but not unintentional) responding (Cummins & De Houwer, 2021).

Present Study

Building on the presented findings the aim of the present thesis is to examine the relationship between students' intelligence mindset and their learning behaviour, while controlling for self-efficacy and anxiety, which can affect motivation in the face of a setback (Elliot & Church, 1997; Elliot & McGregor, 1999; Song et al., 2020). A substantial body of research has shown the possible adaptive influence of growth mindset in an academic achievement context as well as its positive impact on learning outcomes such as grades (Yeager & Dweck, 2020). But to get a more nuanced picture of the mechanism at play in those relationships, it's important to also look at more immediate consequences of growth mindsets, such as behavioural responses to an academic setback. In the face of a failure experience effects of mindset have been shown to become especially influential (see Dweck & Yeager, 2019). In of the only studies looking at direct behavioural responses to a failure experience, students with a growth mindset were more likely to respond with taking remedial action (Hong et al. 1999). Following those findings, it is expected that students endorsing more of a growth mindset will show more engagement with an offered learning opportunity. A supposed failure experience will be created through giving the students feedback on an IQ task in which they have to solve mostly difficult items. Students' behavioural response to this failure experience will be assessed through their engagement with an offered learning opportunity. After they received their feedback, they will be able to choose to review the items from the IQ task.

To accommodate for the mixed findings in recent research on the effects of growth mindset in the academic context (see Costa & Faria, 2018; Sisk et al., 2018) as well as the implicit nature of intelligence beliefs (Dweck & Yeager, 2019), an implicit measure (the above described MT-PEP) will be used to assess intelligence mindset. The combination of looking at direct behavioural outcomes as well as implementing a novel measurement approach might offer a new perspective onto the mixed findings in the existing literature.

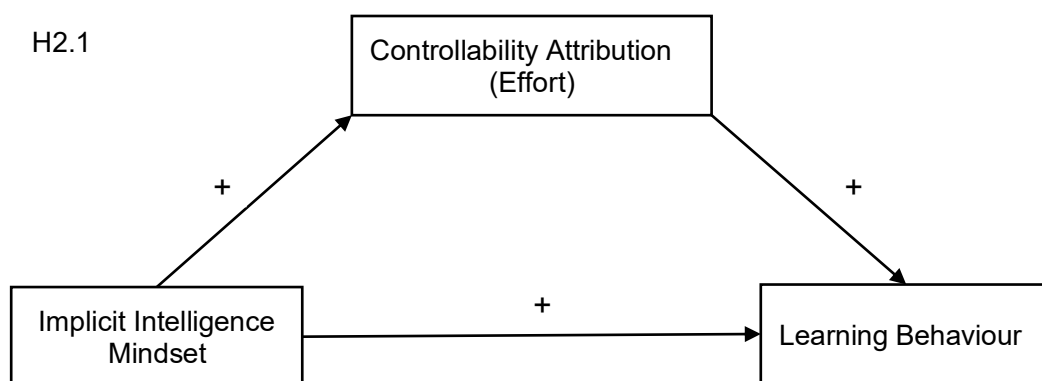
(H1) Subsequently it is hypothesized, that the more students endorse a growth mindset (assessed with an implicit measure), the more solutions (of difficult IQ items they previously worked on) they review.

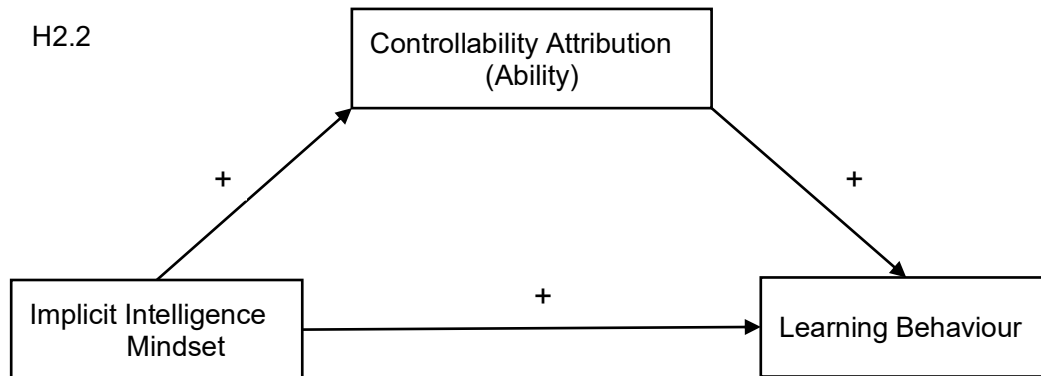
To explain the adaptive influence of growth mindset following a failure experience, students' attributions have been considered as an important factor (Diener & Dweck, 1978; Dweck, 1975; Dweck & Reppucci, 1973; Hong et al., 1999). Especially controllability attribution emerged as a possible influential factor in the relationship between intelligence mindset and academic achievement. A recent study by Song et al. (2020) identified controllability attribution as a mediator between growth mindset and achievement goal adaption. Following those results, it's expected that this mediating influence of controllability attribution will also hold when looking a step further from achievement goals and into behavioural action instead.

(H2) Thus, it is assumed that high scores on growth mindset lead to higher perceived controllability (H2.1) in relation to effort as well as (H2.2) in relation to ability. In turn, higher controllability attributions result in more solutions reviewed as shown in Figure 1.

Figure 1

Proposed Mediation Models





Note. This model shows the proposed relationship between the variables implicit intelligence mindset and learning behaviour mediated by controllability attribution, first in relation to effort (H2.1) and second in relation to ability (H2.2).

Methods

Participants

The sample consisted of students recruited via the LABS-System (Laboratory Administration of Behavioural Science) of the Faculty of Psychology at the University of Vienna. The students were granted course credit for their participation. Following a Monte Carlo power analysis for indirect effects using Schoemann et al.'s (2017) tool in R, we aimed for a sample size of $N = 222$ (Power=.8, $\alpha=.05$). This power analysis was based on the medium effect sizes found by Song et al. (2020). The following exclusion criteria were applied: participants who were non-native German speakers (as the items and instructions were in German), those not currently enrolled as students, individuals with incomplete data on any measures, or those who answered "yes, exclude my data" and provided a valid reason in the self-exclusion question.

220 participants completed the study. Two of those had to be excluded because German wasn't their first language. Additionally, five participants indicated that their data shouldn't be included at the end of the study and another 29 participants had less than 80 % correct answers on the implicit measure and were therefore also excluded.

This resulted in a final sample of 184 participants (76% female, 23% male and 1% other), aged 17 – 55 ($M = 21.3$, $SD = 4.0$).

Study Design and Procedure

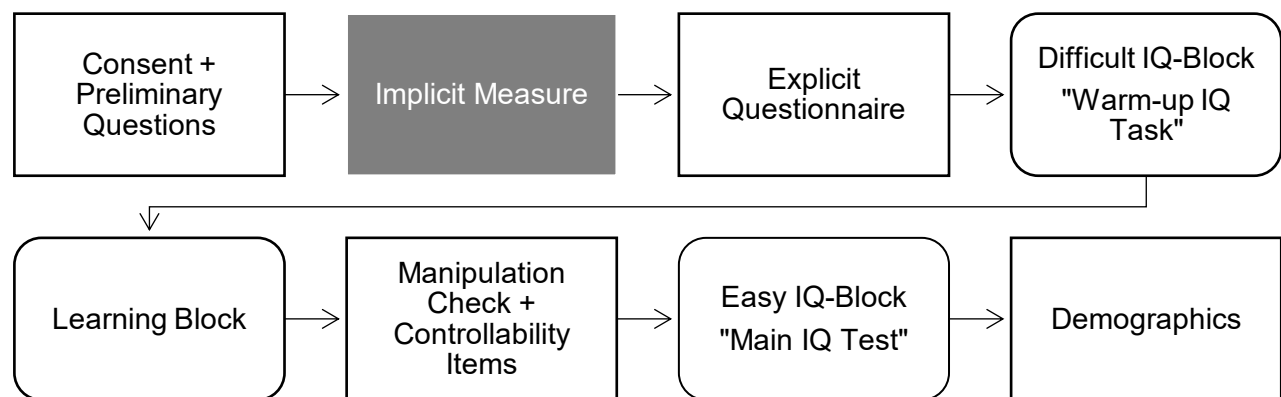
Figure 2 depicts the sequence of the main study procedure blocks relevant to the research question. The study was held at the Social Science Research Lab of the Faculty of Psychology at the University of Vienna throughout October and November of 2021. The entire study was implemented into Qualtrics. At the beginning of the experiment the participants were asked for their consent and had to answer a preliminary questionnaire that checked if they met any exclusion criteria. Furthermore, they were informed that they could leave the study at any point if they wanted to. The experimenter told them, that the purpose of the study was to look at differences in intelligence between different fields of study. They were also asked IQ-related questions such as previous experiences with IQ-tests. Following this they were presented with the second block consisting of the implicit measure, the mouse tracking version of the PEP. After the MT-PEP the participants were presented with the explicit questionnaire including items for intelligence mindset, self-efficacy, and anxiety. Next, in the difficult IQ-block, the participants were told to do a “warm-up IQ task” for the following “main IQ test”. After they completed this task, they were given feedback on how well they performed and how many items they solved. By primarily using extremely difficult items as well as only giving a short time frame (45 seconds) to solve each item, we aimed to create an experience of failure for the participants. With an average of $M = 2.84$ ($SD = 1.58$) out of 12 correctly solved items the overall performance in the “warm-up IQ task” was quite low as intended. To further increase the perception of having failed at the “warm-up IQ task” their results were shown in a red colour. After this supposed failure experience followed a learning block. The participants had the opportunity to choose whether they wanted to review their answers to the test items and look at explanations of possible ways to solve each item. After each solution they were asked if they wanted to continue reviewing the items or move on to the “main IQ test”. As soon as they either finished reviewing all the solutions from the “warm-up IQ task” or chose to move on to the “main IQ test”, they were asked how well they think they did on the “warm-up IQ

task". Following this manipulation check, they were asked about the perceived cause of their performance in the "warm-up IQ task" and their controllability attribution concerning this cause. Then they continued to the easy IQ-block, the "main IQ test", which included easier items and had no time limit. Afterwards they were presented with the second part of the explicit questionnaire (which did not include any scales relevant to this thesis) and demographic items. Lastly the participants were instructed to leave on their own after they finished the last part.

The Study design and data collection was designed and conducted in cooperation with Kata Sik. The findings of this study have been published in Sik et.al. (2024), namely Study 1 of their paper. Due to cooperating on the data collection for this thesis, additional scales have been assessed during the explicit questionnaire block as well as after the "main IQ test" (easy IQ block) which are irrelevant to the research question of this thesis.

Figure 2

Study Procedure (own illustration)



Note. This figure shows the sequence of the different study blocks relevant to this thesis.

Measures

Implicit Measure

Implicit intelligence mindset was assessed via the mouse tracking version of the propositional evaluation paradigm (MT-PEP; Cummins & De Houwer, 2021; Müller & Rothermund, 2019) using six adapted propositions from the intelligence mindset scale by Spinath & Schöne (2003) such as “Everyone has a certain level of intelligence that can be changed.” or “When you learn new things, your intelligence remains the same.”

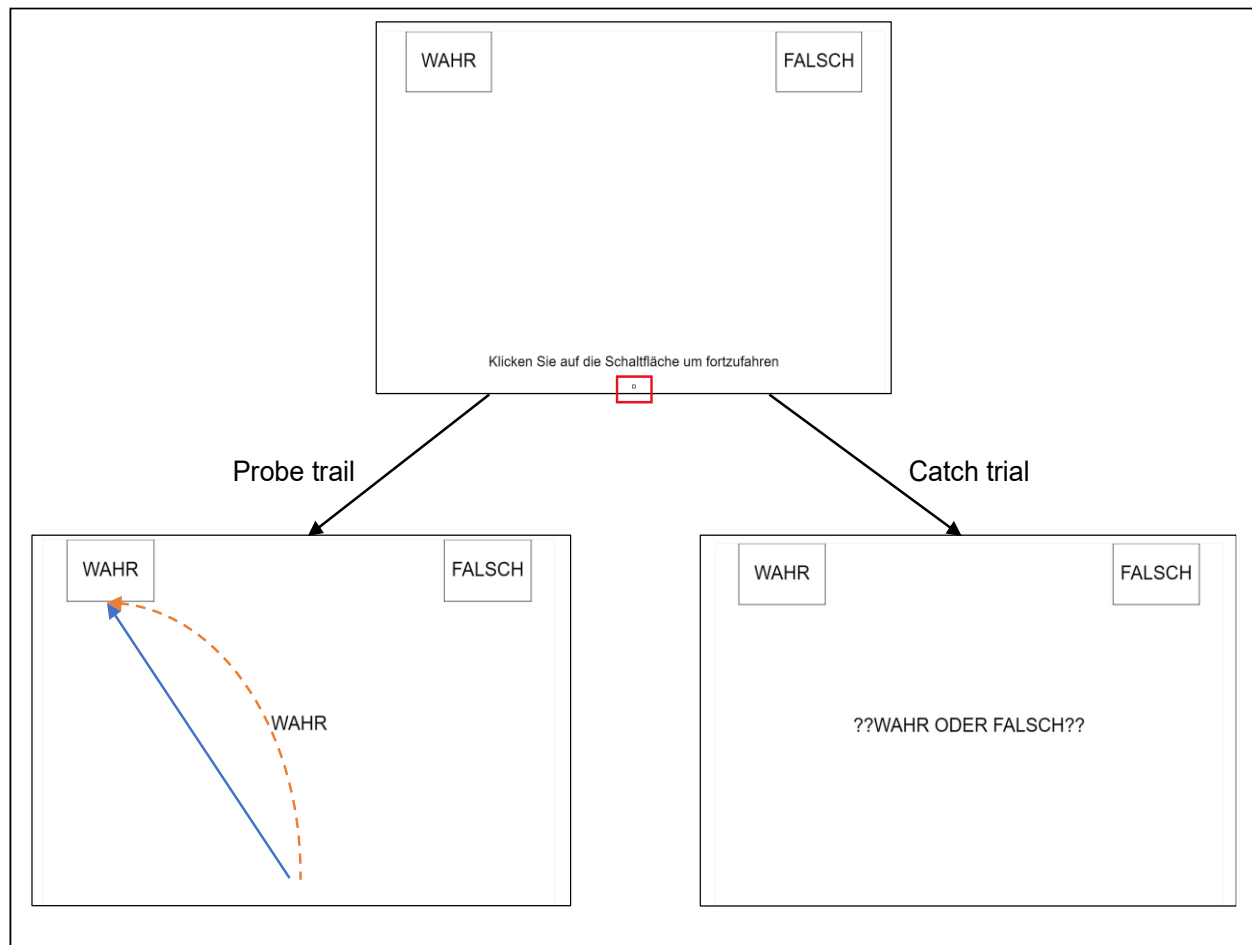
The MT-PEP task includes *probe* and *catch* trials. In a probe trial participants were asked to response to a “TRUE” or “FALSE” prompt, after having been shown the respective proposition (intelligence mindset item) in a word-by-word manner, by moving their mouse to the either top-left (“true”) or top-right (“false”) screen corner. They were instructed to react according to the prompt and irrespective of the shown sentence (e.g. by moving the mouse to “true” after a “TRUE” prompt). In a catch trial (implemented to ensure genuine engagement with the shown propositions) participants were presented with a “??TRUE OR FALSE??” prompt. Now they had to respond according to the spelling of the sentence shown beforehand by moving the mouse to either “true” (spelled correctly) or “false” (spelled incorrectly). Because the catch trials appeared randomly throughout the MT-PEP task and their prompt “??TRUE OR FALSE??” only showed after a proposition was presented, participants had to read every proposition thoroughly. Figure 3 portrays an example of a probe trail and a catch trial in the MT-PEP task.

In the MT-PEP greater deviation from the optimal trajectory indicates a greater tendency to the alternative response (true or false). To quantify this, the area-under-curve (AUC) was assessed. The AUC represents the space between the ideal response trajectory (a direct line from the starting point to the response option) and the participants' time-normalized average trajectories. A higher AUC score signifies a more pronounced shift of the mouse toward the alternative response option (disagreement with the demanded response, e.g., not agreeing with a shown proposition but having to respond to a “TRUE” prompt), indicating an automatic tendency towards that other

response option (e.g., “false” in this example, also shown in Figure 3) (Hehman et al., 2015). The implicit intelligence mindset score was calculated following Cummins and De Houwer’s (2021) paper with higher scores representing more of a growth mindset ($M = 0.02$, $SD = 0.09$). With a split-half reliability coefficient of -0.09 the implicit intelligence mindset measure showed poor internal consistency.

Figure 3

Example of the MT-PEP task (own illustration)



Note. The figure depicts examples of the prompts in the MT-PEP tasks. On the upper part of the screen the buttons for “true” (“WAHR”, top left corner) and “false” (“FALSCH”, top right corner) are located. At the beginning of a trail participants were instructed to click on a small square on the bottom of the screen (framed in red, screen on the top) to start the trail and put the mouse in the right position. Subsequently they were shown a

proposition (intelligence mindset item) in a word-by-word manner in the middle of the screen before they had to react to either a catch or a probe prompt. In the probe trial in this example (screen on the bottom left) they were shown a “true” (“WAHR”) prompt. The blue arrow depicts the neutral or “optimal” mouse movement towards “true” (“WAHR”) whereas the orange arrow shows a deviating mouse movement with a tendency towards the “false” (FALSCH) button. The deviation between the optimal track and the actual mouse movement from the participant creates the area-under-curve (AUC).

IQ-Blocks

The “warm-up IQ task” and the “main IQ test” consisted of adapted items from Raven Progressive Matrices (RPM; Raven & Raven, 2003). The RPM is a non-verbal test that is widely used to assess fluid intelligence or meaning making. The items ask participants to select the correct answer option that completes the shown pattern. In the first IQ block, the “warm-up IQ task”, participants had to solve 12 RPM items starting with a an easy and a medium item (to give them the feeling, that the items are solvable) before being presented with the remaining 12 difficult items. Through only giving them 45 seconds for each item and using relatively difficult items we aimed to create a failure experience for them. Afterwards, participants received feedback on their performance (“In the warm-up task you solved X/12 correctly”) written in red to intensify the feeling of failure. With a mean of 2.84 ($SD= 1.5$) most of the participants didn’t do well on this first IQ block as intended and subsequently rated their performance rather poorly (see below, manipulation check).

In the second IQ block, the “main IQ test”; participants had to solve 12 more RPM items. This time they were presented with four easy, four medium and four difficult items as well as no time limit to give them the chance to solve more items and in turn leaving them with more of a success experience. In this task most of the participants performed quite well ($M = 10.14$, $SD = 1.68$) as expected.

Learning Behaviour

In the learning block we assessed participants' learning behaviour following the supposed failure experience in the "warm-up IQ task". Participants were asked to choose whether they wanted to review the answers they gave in the "warm-up IQ task" and look at possible ways of solving each item or continue to the "main IQ test". After each viewed solution they were again offered to choose to continue reviewing the RPM items or move on to the "main IQ test". If they kept on reviewing, they could look at up to 12 solutions in total. Figure 4 shows an example of a difficult RPM item and the description of a potential way to solve it. To determine the behavioural response to the failure experience, the number of viewed solutions of the RPM items before continuing to the "main IQ test" was counted ($M = 4.62$, $SD = 3.61$).

Figure 4

Example of a difficult Raven Progressive Matrices item (RPM; Raven & Raven, 2003) from the "warm-up IQ task" and the corresponding solution from the learning block (own illustration).

Okay. Du hast geantwortet:

Die Lösung ist:

Spalte 1 Spalte 2 Spalte 3

Reihe 1

Reihe 2

Reihe 3

Es geht um:

- Die **Anzahl an Punkten**, die **Form der Linien** und ihre **Anordnung** muss beachtet werden.
- Reihenweise:
 - je einmal 1, 2, und 3 Punkte pro Figur
 - gleiche Linienform (gerade, gebogen, gewellt)
 - je einmal parallel, in Z-Form, und rechts offene Linienanordnung

Reihe 3

1 Punkt
gewellt
Z-Form

3 Punkte
gewellt
parallel

2 Punkte
gewellt
nach rechts offen

Note. This is an example of a solution from the learning block. On the top left corner, it says “Okay. You answered: [space for the solution previously selected by participant] The solution is:”. Followed by the correct solution as well as the whole RPM item. On the right side one potential way of solving the item is explained. It says: “It is about: The number of dots, the shape of the lines, and their arrangement must be considered. Rowe-wise: - one each with one, two, and three dots per figure; - lines have the same shape (straight, curved, wavy); - each one arrangement in parallel, z-form, and open to the left.”.

Explicit Intelligence Mindset

To explicitly assess the intelligence mindset the same six items were used as for the implicit intelligence mindset task (German translation, Spinath & Schöne, 2003). In contrast to the implicit task the participants were instructed to rate the items on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The mean score of these six items was calculated as the explicit intelligence mindset score, with a higher score indicating a higher growth mindset ($M = 4.15$, $SD = 0.98$). The Cronbach's α coefficient for the intelligence mindsets scale was $\alpha = .85$, indicating a good internal consistency.

Self-efficacy

Self-efficacy was measured via seven items (e.g., “I believe I will succeed in this IQ task”) adapted from the self-efficacy subscale of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich & De Groot, 1990). Participants were asked to rate these items on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The mean score of these seven items was calculated as the self-efficacy score, with a higher score indicating a higher confidence in their intellectual ability ($M = 3.56$, $SD = 0.67$). The scale demonstrated good internal consistency with a Cronbach's α coefficient of $\alpha = .82$.

Anxiety

Anxiety was assessed adopting four items (e.g., “I worry about making mistakes.”) from the Behavioural Inhibition System scale (BIS; Poythress et al., 2008). These items were rated on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The mean score of these four items was calculated as the anxiety score, with a higher score indicating higher anxiety ($M = 4.32$, $SD = 1.03$). With a Cronbach’s α coefficient of $\alpha = .78$, the anxiety scale showed acceptable consistency.

Controllability Attribution

Controllability attribution was measured separate using two adapted items from Russell (1982) in relation to effort and ability similar to Song et al. (2020). First the participants were asked to rate how much they think their performance on the “warm-up IQ task” depended on either effort or ability. Subsequently they rated how controllable they view those (“Abilities/efforts can change if I try to change them” and “Ability/effort is something that I can change.”) on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). For both the mean score of these two items was calculated with higher scores indicating higher perceived controllability either in relation to effort ($M = 4.77$, $SD = 0.86$) or in relation to ability ($M = 3.58$, $SD = 1.10$). The Pearson’s r for controllability attribution in relation to effort was $r = .65$ indicating a less than ideal internal consistency whereas controllability attribution in relation to ability showed good internal consistency ($r = .83$.)

*****IQ related Items*****

Four IQ related questions were used to control for previous experience with IQ-tests, knowledge about participants own IQ-score as well as confidence about and importance of it. Those items included “Has your IQ ever been tested?”, “What was your score?”, “How confident are you in your IQ?” and “How important is your IQ for you?”. The last two were rated on a 6-point Likert scale ranging from 1 (*not at all*) to 6 (*very much*).

Manipulation Check

As a manipulation check, the participants were asked “How well do you feel like you did on this warm-up task?” on a scale from 1 (*very poorly*) to 6 (*very well*). With an average of $M = 1.42$ ($SD = 0.71$) the participants rated their own performance in the “warm-up IQ task” quite poorly indicating that giving them a failure experience succeeded.

Analyses

The entire statistical analysis was done using the data analysis tool JASP (JASP Team, 2022). At first a preliminary analysis of the data was completed. This included descriptive statistics and latent correlations. Because the outcome variable learning behaviour wasn't normally distributed Spearman's rho was used to assess correlations between the different variables. However, Spearman's correlation has its limitations. To test the main effect of implicit intelligence mindset (assessed with the MT-PEP) on learning behaviour (H1) a poisson regression was employed. Due to the non-normality of the outcome variable as well as it being a count variable a poisson regression model is the more appropriate approach. It estimates the probability of event occurrences (in this case: numbers of solutions reviewed) and allows for the inclusion of covariates, which makes it possible to control for additional variables (Cameron & Trivedi, 2013). Additionally, a Goodness-of-Fit test (deviance test) was used to evaluate the fit of the proposed model.

To look at the mediating role of controllability attribution (H2) a mediation analysis through the structural equation modelling (SEM) function in JASP was performed. SEM can be used for the measurement and analysis of relationships of observed and latent variables. It is similar but more powerful than other correlational methods such as regression analyses (Beran & Violato, 2010). Through SEM multiple variables can be analysed while simultaneously accounting for measurement error (Beran & Violato, 2010). In a first mediation analysis controllability attribution in relation to effort was used as a mediator (H2.1) and in a second mediation analysis controllability attribution in relation to ability was used as a mediator (H2.2). To account for non-normality of the

outcome variable here, bias corrected bootstrapping (5000 replications) was implemented.

In an exploratory analysis the same procedures were followed as before but with self-reported explicit intelligence mindset instead of implicit intelligence mindset as a predictor in the poisson regression as well as the two mediation models. This was done to investigate whether using the self-reported mindset scores would produce different results from using the implicitly assessed mindset scores.

Results

Descriptive Statistics and Latent Correlations

Table 1 shows the descriptive statistics and Table 2 the spearman's correlations of the different measures used in this study. Spearman's rho correlation coefficient was used to assess the latent relationships between the variables. There was a significant strong positive correlation between controllability attribution (in relation to ability) and explicit intelligence mindset ($r_s(182) = .52, p < .001$) as well as a significant weak positive correlation between controllability attribution (in relation to ability) and learning behaviour ($r_s(182) = .17, p = .02$). Furthermore, a significant weak positive correlation between self-efficacy and learning behaviour ($r_s(182) = .26, p < .001$) could be found.

Table 1

Descriptive Statistics

Variable	<i>M</i>	<i>SD</i>	Range
Implicit Intelligence Mindset	0.02	0.09	-0.23 – 0.27
Explicit Intelligence Mindset	4.15	0.98	1 – 6
Learning Behaviour	4.62	3.61	0 – 12
Controllability Attribution (Effort)	4.77	0.86	2 – 6
Controllability Attribution (Ability)	3.58	1.10	1 – 6
Anxiety	4.32	1.03	1 – 6
Self-Efficacy	3.56	0.67	1.14 – 5.29

Note. *M* represents the mean and *SD* the standard deviation of each variable observed. Range shows the minimum and maximum values observed for each variable.

Table 2

Spearman's Correlations

Variable	1	2	3	4	5	6
1. Implicit Intelligence Mindset	–					
2. Explicit Intelligence Mindset	-.08 [-.23, .06]	–				
3. Learning Behaviour	.12 [-.02, .27]	.12 [-.03, .27]	–			
4. Controllability Attribution (Effort)	-.02 [-.16, .13]	.07 [-.09, .22]	-.01 [-.16, .13]	–		
5. Controllability Attribution (Ability)	-.01 [-.15, .13]	.52*** [.39, .63]	.17* [.02, .31]	.08 [-.07, .24]	–	
6. Anxiety	.03 [-.13, .18]	.03 [-.12, .17]	.00 [-.14, .15]	-.06 [-.20, .09]	-.02 [-.17, .13]	–
7. Self-Efficacy	-.11 [-.25, .04]	.06 [-.10, .21]	.26*** [.12, .40]	-.01 [-.17, .14]	.03 [-.12, .19]	.08 [-.27, .01]

Note. Spearman's rho was calculated to assess the correlations between the different variables. The 95% confidence interval for each correlation is presented in square brackets.

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

Main Effect of Mindset

A poisson regression was used to examine the main effect of the implicit intelligence mindset (measured via the MT-PEP) on learning behaviour while controlling for anxiety and self-efficacy (see Table 3 for the regression coefficients). A one-unit increase in the implicit measure score (indicating less of a fixed intelligence mindset) was associated with an approximately 3.92 times increase in learning behaviour (number of reviewed solutions) ($p < .001$). The deviance goodness of fit test indicated a significant deviation from the expected model fit. The residual deviance for the model was 490.98 on 179 degrees of freedom ($p < .001$) suggesting a lack of model fit.

Table 3

Poisson Regression Coefficients for Learning Behaviour

	b	SE	z-Value	CI
Implicit Intelligence Mindset	1.37***	0.37	3.65	[0.63, 2.10]
Anxiety	0.05	0.04	1.38	[-0.02, 0.12]
Self-Efficacy	0.29***	0.05	5.48	[0.19, 0.40]

Note. This table shows the regression coefficients (b) for learning behaviour, as well as the respective standard error (SE), z-Value and confidence interval (CI).

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

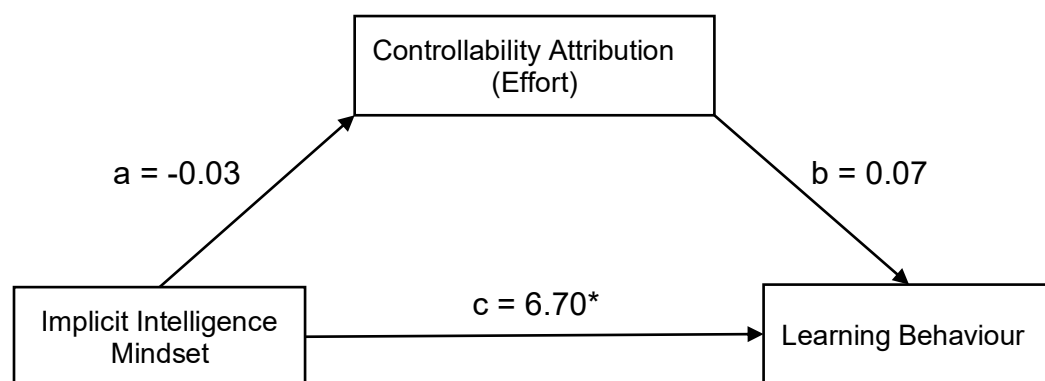
Mediation Effect of Controllability Attribution

To assess the mediating role of controllability attribution, a model was tested implementing implicit intelligence mindset as an exogenous variable and learning behaviour as outcome variable, while controlling for anxiety and self-efficacy. First, controllability attribution in relation to effort as a mediator as shown in Figure 5 was looked at. Employing bias corrected bootstrapping (5000 replications) and a 95 percent confidence interval, a significant direct effect of implicit intelligence mindset on learning behaviour ($c = 6.70$, $SE = 2.88$, $p = .02$, 95% CI [0.94, 12.58]) could be found. This indicates that implicit intelligence mindset significantly predicted learning behaviour,

while controlling for anxiety and self-efficacy. However, no significant indirect effect of implicit intelligence mindset on learning behaviour via controllability attribution ($ab = -0.002$, $SE = 0.05$, $p = .96$, 95% $CI [-0.48, 0.44]$) could be observed. This suggests that controllability attribution in relation to effort did not mediate the relationship between implicit intelligence mindset and learning behaviour. Therefore, while the direct effect remained significant, the absence of a significant indirect effect means that controllability attribution in relation to effort did not explain the relationship between implicit intelligence mindset and learning behaviour. The total effect of implicit intelligence mindset on learning behaviour was also significant ($c' = 6.70$, $SE = 2.88$, $p = .02$, 95% $CI [0.98, 12.65]$). Although a direct effect emerged, the overall model does not support the role of controllability attribution in relation to effort as a mediator because the indirect effect through controllability attribution in relation to effort was not significant.

Figure 5

Mediation model with controllability attribution in relation to effort as a mediator



Note. The mediation model shows the previously hypothesized (H2.1) paths between implicit intelligence mindset, learning behaviour and controllability attribution in relation to effort while controlling for anxiety and self-efficacy (see Table 4 for all path coefficients).

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

Table 4*Path Coefficients*

		b	SE	z- Value	CI
Controllability Attribution (Effort)	→ Learning Behaviour	0.07	0.30	0.25	[-0.50, 0.68]
Implicit Intelligence Mindset	→ Learning Behaviour	6.70*	2.88	2.33	[1.21, 12.90]
Implicit Intelligence Mindset	→ Controllability Attribution (Effort)	-0.03	0.71	-0.05	[-1.42, 1.30]
Anxiety	→ Implicit Intelligence Mindset	0.003	0.01	0.42	[-0.01, 0.01]
Self-Efficacy	→ Implicit Intelligence Mindset	-0.02	0.01	-1.58	[-0.03, 0.01]
Anxiety	→ Controllability Attribution (Effort)	-0.08	0.06	-1.34	[-0.21, 0.03]
Self-Efficacy	→ Controllability Attribution (Effort)	-0.04	0.10	-0.45	[-0.24, 0.17]
Anxiety	→ Learning Behaviour	0.21	0.25	0.83	[-0.32, 0.73]
Self-Efficacy	→ Learning Behaviour	1.32***	0.39	3.43	[0.62, 2.11]

Note. This table shows the path coefficients (b) as well as the respective standard error (SE), z-Value and confidence interval (CI).

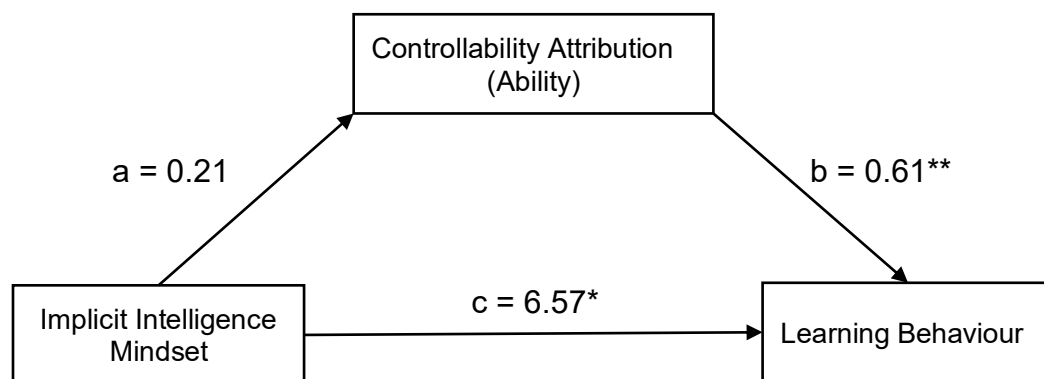
* $p < .05$, ** $p < .01$, *** $p < .001$

Second, the same model but with controllability attributions in relation to ability as a mediator as shown in Figure 6 was looked at. A significant direct effect of implicit intelligence mindset on learning behaviour ($c = 6.57$, $SE = 2.83$, $p = .02$, 95% CI [0.44, 12.24]) could be found. This indicates again that implicit intelligence mindset significantly predicted learning behaviour, while controlling for anxiety and self-efficacy. No significant indirect effect of implicit intelligence mindset on learning behaviour via controllability attribution ($ab = 0.13$, $SE = 0.56$, $p = .82$, 95% CI [-1.05, 1.32]) showed.

This suggests that controllability attribution in relation to ability did not mediate the relationship between implicit intelligence mindset and learning behaviour. Therefore, while the direct effect remained significant, the absence of a significant indirect effect means that controllability attribution in relation to ability did not explain the relationship between implicit intelligence mindset and learning behaviour. This also resulted in a significant total effect of implicit intelligence mindset on learning behaviour ($c' = 6.70$, $SE = 2.88$, $p = .02$, 95% CI [0.71, 12.38]). Although a direct effect emerged, the overall model does not support the role of controllability attribution in relation to ability as a mediator because the indirect effect through controllability attribution in relation to ability was not significant.

Figure 6

Mediation model with controllability attribution in relation to ability as a mediator



Note. The mediation model shows the previously hypothesized (H2.2) paths between implicit intelligence mindset, learning behaviour and controllability attribution in relation to ability while controlling for anxiety and self-efficacy (see Table 5 for all path coefficients).

Table 5*Path Coefficients*

		b	SE	z- Value	CI
Controllability Attribution (Ability)	→ Learning Behaviour	0.61**	0.23	2.68	[0.17, 1.12]
Implicit Intelligence Mindset	→ Learning Behaviour	6.57*	2.83	2.32	[0.80, 12.45]
Implicit Intelligence Mindset	→ Controllability Attribution (Ability)	0.21	0.91	0.23	[-1.57, 2.12]
Anxiety	→ Implicit Intelligence Mindset	0.003	0.01	0.42	[-0.01, 0.02]
Self-Efficacy	→ Implicit Intelligence Mindset	-0.02	0.01	-1.58	[-0.03, 0.01]
Anxiety	→ Controllability Attribution (Ability)	-0.07	0.08	-0.84	[-0.24, 0.10]
Self-Efficacy	→ Controllability Attribution (Ability)	0.06	0.12	0.51	[-0.20, 0.34]
Anxiety	→ Learning Behaviour	0.25	0.25	0.99	[-0.27, 0.74]
Self-Efficacy	→ Learning Behaviour	1.28***	0.38	3.39	[0.59, 2.06]

Note. This table shows the path coefficients (b) as well as the respective standard error (SE), z-Value and confidence interval (CI).

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

Exploratory Analysis

A second poisson regression model using the explicit intelligence mindset scores (self-report) instead of the implicit scores was employed (see Table 6 for regression coefficients). A one-unit increase in the explicit mindset score (indicating less of a fixed intelligence mindset) was associated with an approximately 1.02 times increase in learning behaviour (number of reviewed solutions) ($p = .003$). The deviance

goodness of fit test indicated a significant deviation from the expected model fit. The residual deviance for the model was 495.24 on 179 degrees of freedom ($p < .001$) suggesting a lack of model fit.

Table 6

Poisson Regression Coefficients for Learning Behaviour

	b	SE	z-Value	CI
Explicit Intelligence Mindset	0.12**	0.04	2.94	[0.04, 0.18]
Anxiety	0.05	0.03	1.57	[-0.01, 0.12]
Self-Efficacy	0.27***	0.05	4.99	[0.16, 0.37]

Note. This table shows the regression coefficients (b) for learning behaviour, as well as the respective standard error (SE), z-Value and confidence interval (CI).

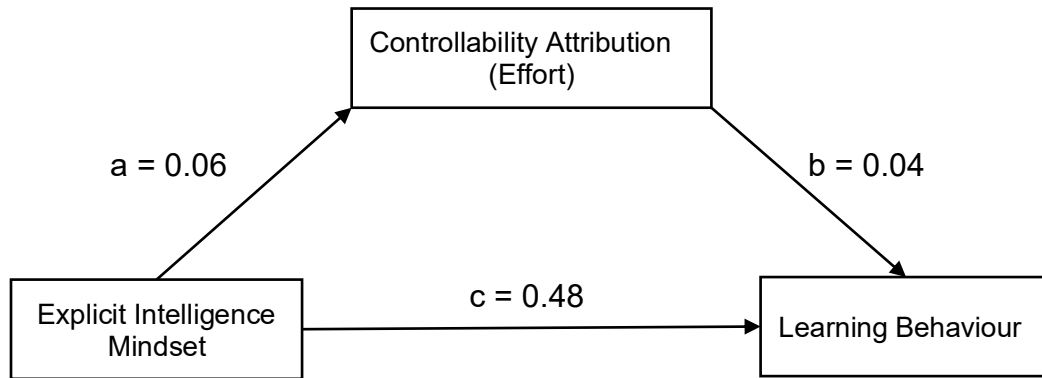
* $p < .05$, ** $p < .01$, *** $p < .001$

To assess the mediating role of controllability attribution, a model was tested implementing explicit intelligence mindset as an exogenous variable and learning behaviour was used as outcome variable, while controlling for anxiety and self-efficacy. First, controllability attribution in relation to effort as a mediator as shown in Figure 7 were investigated. Employing bias corrected bootstrapping (5000 replications) and a 95 percent confidence interval, no significant direct effect of explicit intelligence mindset on learning behaviour ($c = 0.48$, $SE = 0.27$, $p = .07$, 95% CI [0.03, 0.97]) could be found. This indicates that explicit intelligence mindset did not predict learning behaviour, while controlling for anxiety and self-efficacy. Also, there was no significant indirect effect of explicit intelligences mindset on learning behaviour via controllability attribution in relation to effort ($ab = 0.002$, $SE = 0.02$, $p = .91$, 95% CI [-0.05, 0.09]). This suggests that controllability attribution in relation to effort did not mediate the relationship between explicit intelligence mindset and learning behaviour. This resulted in no significant total effect of explicit intelligence mindset on learning behaviour ($c' = 0.49$, $SE = 0.27$, $p = .07$, 95% CI [0.04, 0.97]). Overall, the model does not support the role of explicit

intelligence mindset as a predictor for learning behaviour nor the role of controllability attribution in relation to effort as a mediator.

Figure 7

Mediation model with controllability attribution in relation to effort as a mediator



Note. The mediation model shows the previously hypothesized paths between explicit intelligence mindset, learning behaviour and controllability attribution in relation to effort while controlling for anxiety and self-efficacy (see Table 7 for all path coefficients).

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

Table 7

Path Coefficients

		b	SE	z- Value	CI
Controllability Attribution (Effort)	→ Learning Behaviour	0.04	0.30	0.12	[-0.54, 0.62]
Explicit Intelligence Mindset	→ Learning Behaviour	0.48	0.27	1.80	[0.03, 0.97]
Explicit Intelligence Mindset	→ Controllability Attribution (Effort)	0.06	0.07	0.91	[-0.09, 0.22]
Anxiety	→ Explicit Intelligence Mindset	-0.02	0.07	-0.27	[-0.15, 0.12]

Self-Efficacy	→ Explicit Intelligence Mindset	0.08	0.11	0.73	[-0.12, 0.29]
Anxiety	→ Controllability Attribution (Effort)	-0.08	0.06	-1.32	[-0.20, 0.04]
Self-Efficacy	→ Controllability Attribution (Effort)	-0.05	0.10	-0.50	[-0.24, 0.17]
Anxiety	→ Learning Behaviour	0.23	0.25	0.92	[-0.31, 0.76]
Self-Efficacy	→ Learning Behaviour	1.18**	0.39	3.06	[0.42, 1.96]

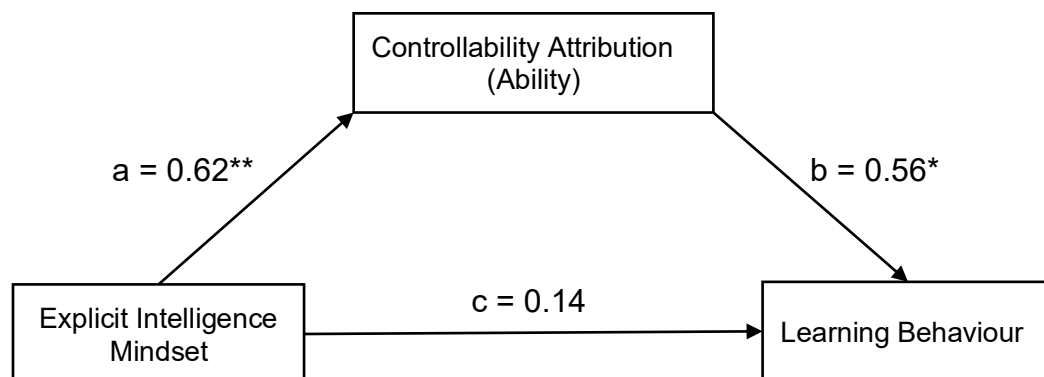
Note. This table shows the path coefficients (b) as well as the respective standard error (SE), z-Value and confidence interval (CI).

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

Second, the same model but with controllability attribution in relation to ability as a mediator as shown in Figure 8 was investigated. No significant direct effect of explicit intelligence mindset on learning behaviour ($c = 0.14$, $SE = 0.32$, $p = .65$, 95% $CI [-0.49, 0.71]$) could be found. This indicates that explicit intelligence mindset did not predict learning behaviour, while controlling for anxiety and self-efficacy. Also, no significant indirect effect of explicit intelligence mindset on learning behaviour via controllability attribution in relation to ability ($ab = 0.34$, $SE = 0.18$, $p = .05$, 95% $CI [0.02, 0.74]$) emerged. This suggests that controllability attribution in relation to ability did not mediate the relationship between explicit intelligence mindset and learning behaviour. This resulted in no significant total effect of explicit intelligence mindset on learning behaviour ($c' = 0.49$, $SE = 0.27$, $p = .07$, 95% $CI [0.02, 0.96]$). Overall, the model does not support the role of explicit intelligence mindset as a predictor for learning behaviour nor the role of controllability attribution in relation to ability as a mediator.

Figure 8

Mediation model with controllability attribution in relation to ability as a mediator



Note. The mediation model shows the previously hypothesized paths between explicit intelligence mindset, learning behaviour and controllability attribution in relation to ability while controlling for anxiety and self-efficacy (see Table 8 for all path coefficients).

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

Table 8

Path Coefficients

		b	SE	z- Value	CI
Controllability Attribution (Ability)	→ Learning Behaviour	0.56*	0.28	2.01	[0.03, 1.13]
Explicit Intelligence Mindset	→ Learning Behaviour	0.14	0.32	0.45	[-0.46, 0.72]
Explicit Intelligence Mindset	→ Controllability Attribution (Ability)	0.62***	0.07	8.72	[0.46, 0.76]
Anxiety	→ Explicit Intelligence Mindset	-0.02	0.07	-0.27	[-0.16, 0.12]
Self-Efficacy	→ Explicit Intelligence Mindset	0.08	0.11	0.73	[-0.13, 0.28]

Anxiety	→ Controllability	-0.06	0.07	-0.82	[-0.19, 0.08]
	Attribution (Ability)				
Self-Efficacy	→ Controllability	0.01	0.10	0.12	[-0.21, 0.24]
	Attribution (Ability)				
Anxiety	→ Learning Behaviour	0.26	0.25	1.05	[-0.25, 0.79]
Self-Efficacy	→ Learning Behaviour	1.18**	0.39	3.06	[0.46, 1.93]

Note. This table shows the path coefficients (b) as well as the respective standard error (SE), z-Value and confidence interval (CI).

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

Discussion

The aim of this thesis was to examine the relationship between implicit intelligence mindset and learning behaviour following a failure experience, while also looking at controllability attribution as a possible mediator of this relationship. In contrast to the majority of the existing literature, intelligence mindset was assessed implementing a novel implicit approach, the MT-PEP, in addition to a self-report measure. While intelligence mindset was able to predict learning behaviour, no mediating effect of controllability attribution (neither in relation to effort nor in relation to ability), could be found.

Effects of Intelligence Mindset on Learning Behaviour

In a poisson regression model, implicit intelligence mindset significantly predicted the number of items reviewed by a participant following a block consisting of mostly very difficult IQ items, while controlling for anxiety and self-efficacy. Consistent with previous studies (Hong et al., 1999; Nussbaum, & Dweck, 2008) participants with a stronger growth mindset demonstrated higher engagement with the offered learning opportunity (choose to review more items) before continuing to the supposed main task. These findings are also in line with research on behavioural self-handicapping. Students primed with a fixed mindset took less advantage of a given learning opportunity after a failure experience by engaging with fewer items (Niiya et al., 2010).

Students endorsing more of a growth mindset tend to adopt mastery goals focusing on improving their abilities (Cury et al., 2006; Dweck & Leggett, 1988) and demonstrate adaptive learning strategies and persistence (Blackwell et al., 2007; Burnette et al., 2013). Thus, growth mindset acts as a buffer against potentially demotivating situations such as an academic failure experience (Aditomo, 2015) and therefore positively influences more general learning outcomes and overall academic success (Yeager & Dweck, 2020).

A second poisson regression model implementing explicit intelligence mindset (assessed via a self-report measure) instead of the implicit intelligence mindset yielded similar results. Explicit intelligence mindset also emerged as a predictor for learning behaviour.

Furthermore, self-efficacy predicted learning behaviour in the above-described model. Students reporting higher levels of self-efficacy were more likely to review more items and therefore showed more persistence during a difficult task. Through seeking challenging tasks, persistence in the face of difficulty as well as adaptation of learning strategies when faced with failure, self-efficacy can promote academic success (Mega et al., 2013). Although only a small effect (Persons' $r = .26$) emerged, this is in line with a recent meta analysis by Honicke and Broadbent (2016) that showed a moderate positive relationship between self-efficacy and academic achievement.

Contrary to what could have been expected from the literature (e.g. Song et al. 2020; Elliot & Church, 1997; Elliot & McGregor, 1999), anxiety did not have any significant influence on learning behaviour nor correlation with any of the other variables.

Interestingly, there was also no correlation between the implicit and explicit intelligence mindset, which opens the questions whether the two measure the same construct. However, a lack of correlation is not that surprising when looking at the generally low correlations between implicit and explicit measurements in the literature (Gawronski & Hahn, 2018; Cameron et al., 2012; Hofmann et al., 2005). Recent theorizing by De Houwer (2014) and De Houwer et al., (2020) suggests that rather the conditions under which the two measures assess the construct differ than the captured

construct itself (Van Dessel et al., 2020). The conditions which vary between the implicit intelligence mindset measure (MT-PEP) and the self-report of the explicit intelligence mindset are mainly the level of processing of and engagement with the beliefs as well as the required speed of responding to these beliefs. In the MT-PEP, students had to only engage with the beliefs so far as to thoroughly read the given statements to be able to answer in the catch trials whether they had a spelling error instead of focusing on their meaning. This led to rather automatic and “unaware” responses throughout the whole implicit task. Whereas in the explicit self-report students had to properly engage with and process the given statements in order to evaluate how much they agree with them, leading to a more thought out and deliberate response. This leads back to the earlier discussed so called “false growth mindset” (Dweck, 2015, 2016). The observed mismatch between teachers self-reported growth mindset and their behaviour might stem from other beliefs being at work, instead of being a result from introspective limits or familiarity with the concept. Teachers might react “automatically” with praise to a student’s success, although in hindsight they realize it would have been better to praise the student’s effort (consistent with growth mindset). In line with Fazio (1990), explicit measures such as self-reported growth mindset might be better predictors for deliberate action, such as deliberately praising a student’s efforts while being mindful of the effect praise can have on a student’s own mindset. On the other hand, implicit measures such as the implicit intelligence mindset might be more effective when predicting rather direct and “unaware” responses to a situation.

Academic success is dependent on both automatic responses, such as immediate reactions to challenges in the classroom or staying persistent in a test after failing to solve an item, as well as more deliberate actions, such as making study plans and adapting learning strategies throughout the semester. Therefore, a multimodal approach might be more practical in studying the involved motivational processes and getting a better understanding of the different variables at play.

Controllability Attribution as a Possible Mediator between Mindset and Learning Behaviour

Controllability attribution did not significantly mediate the relationship between growth mindset and learning behaviour (neither in relation to effort nor in relation to ability) in a mediation SEM model. These findings contradict those of Song et al. (2020), who showed controllability attribution as a mediator in the relationship between growth mindset and achievement goal adoption following a failure experience in a similar achievement context. One possible explanation could be differing outcome variables. In this work, a direct behavioural response was assessed instead of achievement goal adaption. Responding to an achievement goal questionnaire might elicit a more deliberate and thought-out response than actually engaging with a learning task such as choosing to review items - a rather automatic and less deliberate response. Moreover, there might be multiple motivational and cognitive processing variables at play in the translation from achievement goal adaption into direct behavioural action and subsequently academic performance (see Grant & Dweck, 2003). Self-regulation mechanisms, such as effort regulation and persistence, might influence this relationship (Duckworth et al., 2010). Additionally, cognitive properties such as working memory capacity and attentional control, might have an impact on how achievement goals translate into behaviour (Schmidt & De Houwer, 2012).

Furthermore, controllability attribution was split into controllability attribution in relation to effort and in relation to ability, to offer a more differentiated assessment. Song et al. (2020) on the other hand, asked their participants whether they attributed their failure to a lack of ability or a lack of effort and then had them rate the controllability in relation to what they had previously chosen. Therefore, slightly differing constructs might have been assessed. Students might have differing meanings in mind when it comes to effort and ability attributions and therefore vary in their way of conceptualizing controllability in relation to effort or ability. Hong et al. (1999) showed that depending on their mindset, students showed different patterns of effort and ability attributions. Students endorsing a fixed mindset attributed their performance more to ability than to effort, while students in the growth mindset group showed weaker ability and stronger

effort attribution. However, when only looking at the growth mindset group, students attributed their failure as much to their effort as to their ability, which might indicate that the two might hold a different meaning depending on the mindset. Subsequently this might lead to differing conceptualizations of controllability attribution in relation to effort and in relation to ability, which might be better represented in splitting the two. That way an underlying influence of mindset on attributing the failure to one or the other as well as possible differing meanings effort and ability hold for students, are better accounted for.

Although no mediating role of controllability attribution could be observed, controllability attribution in relation to ability showed a significant effect on learning behaviour in both SEM models. Students, who attributed their intellectual ability to a greater extent to be something under their control to change, showed higher engagement with the learning task. Believing one's own intellectual abilities to be under one's personal control to be changed is linked to behavioural adjustment, including students' intentions to act as well as the self-regulation strategies they plan to implement (e.g. short term persistence on a task, Le Foll et al., 2006) and consequently academic performance (Brun et al., 2021).

Furthermore, a significant effect of explicit intelligence mindset on controllability attribution in relation to ability emerged. The more students endorsed a growth mindset (assessed with a self-report measure), the more they viewed their intellectual abilities to be under their personal control to be changed. High agreement with the belief, that one's own intelligence is changeable, and the attribution, that changing the corresponding intellectual abilities is under one's own control, are closely related. This relationship has been described as one potentially important factor in explaining the adaptive influence of growth mindset when facing a setback (Diener & Dweck, 1978; Dweck, 1975, Dweck & Reppucci, 1973; Hong et al., 1999; Song et al., 2020; Weiner, 1986, 2010).

Even though explicit intelligence mindset significantly predicted learning behaviour in the above described poisson regression model, it showed no significant direct effect on learning behaviour in the mediation models. One possible explanation

could be that while poisson regression estimates the direct effect of the predictor on the outcome, SEM (used for the mediation analysis) uses latent constructs and accounts for measurement error, which can lead to weakened associations due to more conservative estimates (Kline, 2015). Furthermore, the simultaneous estimation of multiple parameters in SEM can lead to reduced statistical power compared to simpler models (Hayes, 2018). This becomes particularly relevant when comparing results across different analytical approaches. The same predictor may exhibit significant effects in simpler models, such as a poisson regression, but might emerge as nonsignificant in more complex SEM frameworks as the employed SEM mediation models (MacKinnon, 2008). Additionally, SEM models typically require larger sample sizes to show effects reliably (Preacher & Hayes, 2008). If the sample size is relatively small, as in the given sample ($N = 184$), standard errors increase, which reduces significance. This becomes apparent when looking at the mediation model with controllability attribution in relation to effort as a proposed mediator. In this model, the direct effect of explicit intelligence mindset on learning behaviour was not significant, but the corresponding confidence interval did not include zero ($CI [0.03, 0.97]$). This suggests that, while the effect is present, it is small and lacks strong statistical support.

Implications

This work adds to the existing literature on the influential role that growth mindset can play for a student's academic success (see Yeager & Dweck, 2020), especially when faced with challenges or setbacks (Hong et al., 1999; Nussbaum & Dweck, 2008; Paunesku et al., 2015). By looking at direct behavioural responses following a failure experience instead of just assessing constructs such as achievement goal adaption (e.g. Song et al., 2020) or more global academic outcomes such as grades (e.g. Blackwell et al., 2007; Yeager et al., 2019), it broadens the understanding of the adaptive influence growth mindset can have on a student's academic success.

Furthermore, through implementing a novel implicit measure (the MT-PEP) to assess intelligence mindset, which showed to be predictive for learning behaviour, new directions for mindset research might be promoted through implying that self-report measures alone might not fully capture the whole construct. Looking at the

heterogeneous findings on the subject (e.g. Costa & Faria, 2018; Sisk et al., 2018), a more nuanced approach to assessing growth mindset seems necessary. A multimodal approach, implementing both implicit and explicit ways of measuring growth mindset, might help get a better understanding of the different processes (and their different levels of inherent awareness) that lead to holistic outcomes such as academic success.

Although the observed relationship is rather modest (Person's r of 0.12, see Table 2), it still holds practical significance within the context of educational psychology. As emphasized by Hill et al. (2008), effect sizes in educational research should be interpreted relative to the specific benchmarks of the field and their broader implications, rather than solely based on statistical thresholds. In the academic setting, learning behaviours cumulate over time and might lead to substantial differences in general academic performance and success. Therefore, the observed correlation emphasises the modest yet meaningful relationship between a student's implicit growth mindset and their behaviour in response to failure.

Limitations and Implications for Future Research

When looking at the findings of this thesis, several limitations must be considered. Although the implicit measure showed to be predictive for learning behaviour, its poor internal consistency can not be ignored. Assessing mindsets with an implicit measure has proven to be difficult in past studies (Meissner et. al., 2019). Poor measurement properties are not uncommon for implicit measures (Gawronski & De Houwer, 2014) and might limit the utility of implicit measures in predicting reliable effects. For future use of the MT-PEP the number of trails could be increased to boost internal consistency. Additionally, considering the lack of correlation between the implicit and explicit measure future research could implement the truth evaluation variant of the MT-PEP instead of the spelling-error variant. In contrast to judging whether there was a spelling error in the presented sentence (in a catch trail), participants would have to evaluate the truth value of the presented sentence. Cummins & De Houwer (2021) showed that when using the truth evaluation variant, the MT-PEP significantly predicted self-reported beliefs. It's also important to note that the MT-PEP is implicit in the sense of "fast", but participants could intentionally fake beliefs (Cummins & De Houwer, 2021).

Nevertheless, this work showed the potential of using the MT-PEP to implicitly assess growth mindset and future studies might improve and further develop its implementation to make it more reliable.

Considering the rather bad fit of the poisson regression model, the results from this analysis must be treated with caution. One possible explanation for the bad model fit might be an excessive amount of zeros in the outcome variable (number of items reviewed). Implementing a hurdle model (Heilbronn, 1994; Mullahy 1986) could be a more appropriate approach for the analysis. In the case of this work, this would mean first examining if growth mindset predicted the choice to review any items at all. In a second model one would only include the students that choose to review at least one item and look at whether the number of reviewed items was predicted by growth mindset.

Furthermore, there are a few aspects of the study design that must be considered with regards to the generalizability of the observed results. Since the study took place at the Social Science Research Lab of the Faculty of Psychology at the University of Vienna, there might have been different contextual influences at play compared to a real educational context. It might be interesting to investigate how the observed effects translate outside of a lab in a real-world educational setting. Participants' definition of intelligence can be highly context and domain specific (Limeri et al., 2020). Students may hold for example different mindsets, when it comes to their math abilities versus their general intelligence (Shively & Ryan, 2013). Looking at the effects of growth mindset in various educational contexts might help to get a more nuanced insight into when and how growth mindset influences students' learning behaviour.

Also, the participants were told they could leave on their own after finishing the study. This could have had an additional confounding influence on the number of items they reviewed in the learning block. Maybe they had somewhere else to be after the study and didn't review any or many items just to be done as fast as possible.

Additionally, due to the sample mainly consisting of Austrian or German female psychology students with an average age of 21, the results might not be representative

for a more diverse population. Sun et al., (2021) observed cultural differences between US students and Chinese students in the effects of growth mindset on motivation and academic success, indicating the need for research looking at samples from different cultural backgrounds to broaden the understanding of differing effects of growth mindset.

Conclusion

The objective of this thesis was to investigate the relationship between intelligence mindset and learning behaviour after failure, with a focus on controllability attribution as a potential mediator. Both implicit and explicit measures of growth mindset predicted learning behaviour, but controllability attribution did not mediate this relationship. These findings highlight the role growth mindset plays in students' response to a failure experience. The implementation of the MT-PEP as an implicit measure introduced a novel perspective on intelligence mindset, that might not be captured by self-report measures. While promising, its low internal consistency highlights the need for further refinement. Additionally, the lack of correlation between implicit and explicit measures points to the value of using multiple approaches to fully capture the complexity of beliefs.

Although the observed effect sizes were modest, their practical implications in educational contexts are significant. Persistence in the face of failure can cumulate to meaningful academic gains over time. However, limitations such as the homogeneity of the sample and the laboratory setting call for caution when generalizing these findings. Future research should explore the effects of mindset across more diverse populations and real-world contexts, as well as investigate cultural and domain-specific differences. This work highlights the importance of growth mindset in promoting adaptive learning behaviours and provides a starting point for further studies implementing implicit measures to look into the processes and contexts that shape its influence.

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Abbreviations

MT-PEP	Mousetracking Propositional Evaluation Paradigm
AUC	area-under-curve
RPM	Raven Progressive Matrice
SEM	Structural Equation Modelling

Abstract

This thesis explores the relationship between intelligence mindset and learning behaviour following a failure experience, while also looking at controllability attribution as a potential mediator. Contrary to the majority of the existing literature, intelligence mindset was assessed using both a novel implicit measure, the MT-PEP, and a traditional self-report. While both implicit and explicit growth mindset (the belief, that intelligence is changeable) predicted learning behaviour, controllability attribution (in relation to effort or ability) did not mediate this relationship. Findings revealed that university students ($N = 184$) with stronger implicit growth mindsets reviewed more items after a difficult task, suggesting greater engagement with learning opportunities. Explicit growth mindset showed similar effects. Self-efficacy also predicted learning behaviour, while anxiety did not significantly influence outcomes. Notably, implicit and explicit mindset measures were uncorrelated, reflecting complementary dimensions of mindset assessment. Contrary to expectations, controllability attribution did not mediate the relationship between growth mindset and learning behaviour. This study contributes to the growing body of research on mindset by demonstrating the value of implicit measures, shedding light on the interplay between beliefs and behaviour, and suggesting that using both implicit and explicit measures offers a broader understanding of motivational processes involved in academic achievement. Limitations, such as measurement challenges and sample diversity, are discussed alongside implications for educational research and future research directions.

Keywords: implicit measures, growth mindset, controllability attribution, motivation and learning, academic failure

Abstract (German)

Ziel dieser Arbeit ist es den Zusammenhang zwischen Überzeugungen bezüglich Intelligenz (Intelligenz-Mindset) und dem Lernverhalten nach einem Misserfolgserlebnis zu untersuchen. Im Zuge dessen wird auch die Attribution von Kontrollierbarkeit als potenzieller Mediator mit einbezogen. Im Gegensatz zum Großteil der bestehenden Literatur, wurde das Intelligenz-Mindset sowohl mit einem neuartigen impliziten Messinstrument, dem MT-PEP, als auch mit einem traditionellen Selbstbericht erfasst. Während sowohl das implizite als auch das explizite Growth Mindset (die Überzeugung, dass Intelligenz veränderbar ist) das Lernverhalten vorhersagten, mediierte die Attribution von Kontrollierbarkeit (in Bezug auf Anstrengung oder Fähigkeit) diese Beziehungen nicht. Die Ergebnisse zeigten, dass Studierende ($N = 184$) mit einem stärkeren impliziten Growth Mindset mehr Aufgaben nach einer schwierigen Aufgabe bearbeiteten, was auf eine verstärkte Auseinandersetzung mit den gegebenen Lernmöglichkeiten hindeutet. Das explizite Growth Mindset zeigte ähnliche Effekte. Selbstwirksamkeit sagte ebenfalls das Lernverhalten voraus, während Ängstlichkeit keine signifikanten Einflüsse zeigte. Nennenswert ist außerdem die mangelnde Korrelation zwischen implizite und explizite Mindset-Messungen, was auf komplementäre Dimensionen der Mindset-Erhebung hindeutet. Entgegen den Erwartungen vermittelte die Attribution von Kontrollierbarkeit nicht die Beziehung zwischen Growth Mindset und Lernverhalten. Diese Studie leistet einen Beitrag zur wachsenden Zahl von Forschungsarbeiten zum Thema Intelligenz Mindset, indem sie den Wert impliziter Messverfahren aufzeigt, das Zusammenspiel zwischen Überzeugungen und Verhalten beleuchtet und nahelegt, dass die Verwendung sowohl impliziter als auch expliziter Messverfahren ein umfassenderes Verständnis der motivationalen Prozesse ermöglicht, die an akademischen Leistungen beteiligt sind. Einschränkungen, wie Herausforderungen bei der Messung und die mangelnde Diversität der Stichprobe, werden ebenso diskutiert wie Implikationen für Bildungsforschung und zukünftige Forschungsrichtungen.

Schlüsselwörter: implizite Messungen, Growth Mindset, Attribution von Kontrollierbarkeit, Motivation und Lernen, akademisches Versagen