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From beliefs to behaviors: Conceptualizing and assessing students' practices that reflect a growth mindset

Norman B. Mendoza[1] · **Zi Yan**[1]

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Abstract
Current growth mindset models lack the specificity regarding behavioral mechanisms that translate incremental beliefs into meaningful achievement gains. Addressing this gap, this study synthesized the literature to conceptualize the Integrated Growth Systems Framework (IGSF) and developed the Growth Practices Scale (GPS). The IGSF maps how a growth mindset manifests in six effort-based learning practices that influence learning achievement. The GPS, developed to measure these practices, underwent psychometric evaluation using cross-sectional (N = 1150) and longitudinal (n = 575) data from undergraduate students. Factor and network analyses supported a two-factor structure with proactive and reflective growth practices. The 11-item GPS demonstrated reliability, structural validity, and within-person longitudinal measurement invariance. It also showed nomological validity through positive relations with motivated learning strategies, mastery approach goals, and academic resilience. Crucially, the GPS exhibited incremental validity in predicting achievement scores, while accounting for growth mindset beliefs. This research advances growth mindset theory by mapping and measuring behaviors that *enable* the effects of growth mindset beliefs. The IGSF and GPS allow for further empirical examination of the mindset-to-achievement link, offering directions for growth mindset interventions that also target growth-oriented behaviors and strategies. Limitations and future research directions are discussed.

Keywords Implicit theories of intelligence · Growth mindset · Integrated framework · Growth practices · Instrument validation · Achievement

✉ Norman B. Mendoza
nbmendoza@eduhk.hk

Zi Yan
zyan@eduhk.hk

[1] Department of Curriculum and Instruction, Faculty of Education and Human Development, The Education University of Hong Kong, Room 6A, D2/1F, 10 Lo Ping Road, Tai Po, New Territories, Hong Kong SAR, China

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1 Introduction

The concept of growth mindset has been a focal point in educational and psychological research. Rooted in the implicit theories of intelligence, individuals with a growth mindset or incremental views on abilities believe that their intelligence and other personal attributes are not fixed and can be developed through effort (Chiu et al., 1997; Dweck, 2017; Dweck et al., 1995). Aside from approaching challenging tasks (Qin et al., 2021; Rege et al., 2021; Yeager et al., 2016), learners with a growth mindset are often characterized by a wide range of mastery-oriented behaviors like proactive strategies (Blackwell et al., 2007; Yan et al., 2014), perseverance (Bettinger et al., 2018; Lam & Zhou, 2020), and coping adaptively (Parada & Verlhiac, 2022). Adopting a growth mindset influences adaptive and lifelong learning outcomes, such as learning and achievement (Bernardo, 2022; Blackwell et al., 2007; De Castella & Byrne, 2015; Karlen et al., 2021; Yeager et al., 2019), self-regulated learning (Bai & Wang, 2020; Bai et al., 2021; Burnette et al., 2013; Yan et al., 2014, 2021), and even well-being and resilience (Brooks et al., 2012; Yeager & Dweck, 2012; Zeng et al., 2016). Because of the implications that growth mindset beliefs hold for students, even the Programme for International Student Assessment (PISA) started assessing growth mindset (OECD, 2019).

However, as the literature on growth mindset proliferated, so did the criticisms and debates surrounding its theoretical process model, measurement, and broader efficacy (see Burgoyne et al., 2020; Macnamara & Burgoyne, 2022; Sisk et al., 2018; Yan & Schuetze, 2023). A central point of contention has been the clarity of the process model that elucidates how a growth mindset influences academic achievement (see Burgoyne et al., 2020; Macnamara & Burgoyne, 2022, 2023; Sisk et al., 2018; Yan & Schuetze, 2023). Specifically, there is a lack of clarity behind the mechanisms that enable a growth mindset to (in)directly predict academic achievement. Yan and Schuetze, (2023) summarized current models of growth mindset and emphasized that while academic outcomes are often the primary focus of growth mindset interventions, the pathway linking the adoption of a growth mindset to academic achievement remains a *black box* and has not been clearly defined. This gap underscores the pressing need for an integrated framework elucidating the behavioral mechanisms bridging growth mindset with academic outcomes.

While earlier frameworks emphasized behavioral mechanisms (see Blackwell et al., 2007), more recent models shifted focus to cognitive factors (e.g., Yeager & Dweck, 2020). This shift ostensibly responded to conceptual criticisms about direct links between mindsets and outcomes by positioning cognitions as intermediary mechanisms (Burnette et al., 2013; Sisk et al., 2018). This departure from behavioral mediators, however, does not align with the conceptual foundation of mindset theory, which contends that incremental beliefs manifest in effort and actions (Dweck, 1999, 2017). The exclusion of behavioral factors in favor of cognitive ones deviates from the core premise that mindsets shape achievement through change in behavior. With emerging studies demonstrating behavioral mediators (e.g., effort expenditure, proactive coping, metacognitive strategies; Bostwick et al., 2017; Chen et al., 2020; Dupeyrat & Mariné, 2005; Lam & Zhou, 2020; Parada & Verlhiac, 2022), this provides both empirical and conceptual rationale for the examination of behavioral mechanisms within growth mindset frameworks (see Burnette et al., 2022; Macnamara & Burgoyne, 2023). In doing so, a much-needed clarity would be placed on the mechanisms that can explain the mindset-to-achievement link.

By consolidating the empirical research on the behavioral indicators of growth mindset, this study aims to (1) specify the framework of growth mindset that articulates key behavioral practices linking mindset to achievement; and (2) develop and validate an instrument that can assess such practices. In addition to offering significant advancements in the development of the growth mindset theory, the clarity of a framework focused on behavioral mediators responsible for the downstream effects of growth mindset on learning also provides a theoretical framework that can inform the development of a scale to assess growth mindset behaviors or practices (see Abós Catalán et al., 2018; Dawson et al., 2023, for studies that put forth process models to theoretically inform scale development).

Examining students' growth mindset behaviors is crucial for several reasons. First, given that students may report a growth mindset but may not always engage in growth-oriented practices and strategies (see Barger et al., 2022; Dweck, 2015, on "*false growth mindset*"), exploring and assessing learning behaviors helps identify potential belief-behavior gaps. Second, with evidence suggesting that teachers' growth mindset behaviors could shape students' mindsets and learning outcomes (Canning et al., 2022; Yeager & Dweck, 2012; Yeager et al., 2019), identifying behavioral markers of students' growth mindsets can provide insight into the mechanisms over which students influence each other's mindset (King, 2019). Finally and importantly, identifying these behaviors can serve as potential entry points to inform interventions, especially when standard growth mindset interventions yield limited or null effects (see Li & Bates, 2020; Macnamara & Burgoyne, 2022; Sisk et al., 2018; Yeager et al., 2022). Thus, examining students' growth mindset behaviors is essential to clarify the mechanisms by which growth mindsets impact achievement, yielding important implications for growth mindset measurement, theory, and interventions.

1.1 Behavioral mechanisms of growth mindset: an integrated framework

The theoretical landscape of the growth mindset has been the subject of extensive research, with a reasonable consensus emerging around its predictive influence on academic performance. This influence is facilitated by motivational outcomes (e.g., mastery goals) and/or behavioral learning strategies (e.g., increasing focus on tasks; Blackwell et al., 2007; Burnette et al., 2013, 2022; Yan & Schuetze, 2023; Yeager & Dweck, 2020). Blackwell et al., (2007) pioneered empirical investigations into the role of growth mindset in fostering adaptive academic behaviors. Their longitudinal findings highlighted that students with a growth mindset showed increased achievement over time, particularly in challenging academic domains (i.e., mathematics).

Aligned with the seminal work of Dweck and Leggett, (1988), they attributed the increase in achievement to students' tendency to seek challenges, coupled with persistence and resilience in adversities.

Subsequent research has advanced process models of growth mindset, elucidating how specific strategies and behaviors enable the pathways through which growth mindset shapes learning achievement (e.g., Blackwell et al., 2007; Bostwick et al., 2017; Chen et al., 2020; Lam & Zhou, 2020; Parada & Verlhiac, 2022). While recent meta-analyses and theoretical models have attempted to clarify these pathways (e.g., Burnette et al., 2022, for the Mindset Intervention Effectiveness Model; see also Canning & Limeri, 2023), they often lack construct specificity, particularly in defining and measuring mindset-related behaviors. Many existing instruments rely on broad, generalized assessments that do not clearly operationalize behavioral indicators, leading to inconsistencies in how constructs such as 'effort' or 'persistence' are defined across studies (Macnamara & Burgoyne, 2023). Furthermore, these measures tend to isolate cognitive and behavioral components rather than capturing their dynamic interplay in learning contexts (Yan & Schuetze, 2023). This ambiguity hinders our ability to accurately assess and understand the mechanisms through which growth mindset influences academic outcomes. Addressing this gap requires developing more precise definitions and measures of the behavioral manifestations of growth mindset, which would allow for a more nuanced examination of how these beliefs translate into behaviors that ultimately affect achievement.

The process model of growth mindset that ties behavioral mechanisms linking growth mindset to achievement. Solid black arrows represent direct effects, dashed black arrows represent intermediary effects, and dashed grey lines represent distal effects.

Before looking into specific mechanisms, it is crucial to clarify our conceptualization of 'behaviors' within this framework. We adopt a broad definition, encompassing both overt (visible) and covert (invisible) actions that students can engage in or have autonomous control over (Schunk & Greene, 2017). This includes not only observable actions but also internal cognitive and metacognitive processes that manifest in learning contexts (Pintrich, 2000; Efklides, 2011; Zimmerman, 2002). For instance, while metacognitive strategies like planning or self-reflection may not be directly observable, they are considered behaviors or practices as they represent active, controllable processes that students engage in (Chen et al., 2020; Veenman et al., 2006). This definition aligns with our focus on growth mindset behaviors, which include both cognitive strategies and observable learning actions (e.g., reappraisal and self-reflection; Blackwell et al., 2007; Chen et al., 2020; Dweck & Yeager, 2019). Such an inclusive approach allows us to capture the full range of growth-oriented practices, from visible efforts like challenge-seeking (Bettinger et al., 2018; Rege et al., 2021) to more internal processes like adaptive coping strategies (Burnette et al., 2020; Yeager & Dweck, 2012).

Consolidating the recent empirical research on behavioral indicators, as depicted in Fig. 1, we introduce the Integrated growth systems framework (IGSF). While our approach resonates with the meta-analytic model presented by Burnette et al. (2022) and is further enriched by the systems and ecological frameworks (Eccles & Wigfield, 2020; Skinner et al., 2022; see Fig. 1, panel A), it distinctively charts the

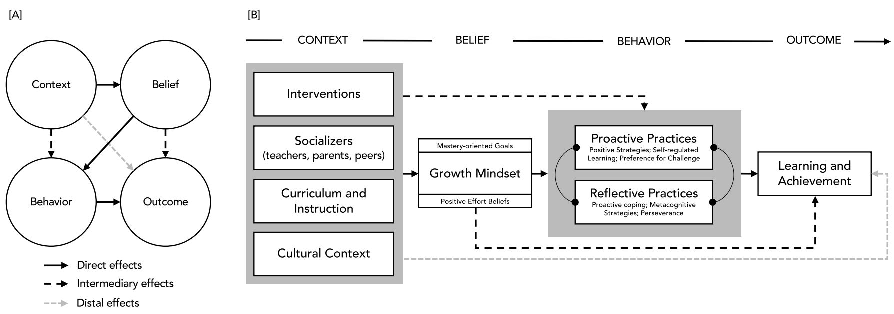

Fig. 1 The Integrated Growth Systems Framework

sequential pathways elucidating the link between mindset and achievement. By integrating previously theorized frameworks with empirical studies that examined the behavioral mediators of mindset to achievement, we delineated how growth mindsets (as beliefs) *enable* the use of learning strategies and practices (as behaviors), culminating in enhanced academic achievement (as outcomes). Moreover, although the focus of the framework is on growth-oriented practices, we also included the role of context on mindset and its outcomes. Specifically, we specified contextual predictors that can potentially have distal or conditional effects on outcomes (e.g., interventions, socializers, learning and instruction, and culture; Bostwick et al., 2020; Canning & Limeri, 2023; Canning et al., 2022; King, 2019; Lou & Noels, 2019; Zeng et al., 2016). Sequentially, the model posits that contexts, beliefs, and behaviors would have distal, intermediary, and direct effects on achievement, respectively (see Fig. 1, panel B). Below, we detail each of these effects.

1.1.1 Distal effects

The distal effects in the IGS framework represent the broader environmental and sociocultural influences that shape one's mindset and learning experiences. These factors include interventions, socializers (e.g., peers, parents, teachers), curriculum and instruction, and cultural context. Growth mindset interventions, whether brief or sustained, can influence students' beliefs about intelligence and learning (Yeager et al., 2019). These interventions often serve as the initial trigger for adopting a growth mindset. For socializers, parents (Hu & Zhang, 2024; Lee et al., 2022), teachers (Kroeper et al., 2022a, 2022b; Laine & Tirri, 2023; Yeager et al., 2022), and peers (King, 2019), play crucial roles in shaping students' mindsets through their own beliefs, expectations, and practices reflecting their growth mindsets (see also Haimovitz & Dweck, 2017). Further, the structure of curriculum and pedagogical approaches can either support or hinder the development of a growth mindset (Cai et al., 2023; Yan et al., 2021). Finally, the broader cultural values and norms regarding intelligence, learning, and achievement can significantly influence the adoption and expression of growth mindset (Bernardo et al., 2021; Chen et al., 2024; Lou & Li, 2023; Sun et al., 2021).

1.1.2 Intermediary effects

Although a growth mindset on its own could impact behavioral learning strategies, it can also modulate related motivational outcomes, which subsequently shape learning strategies (e.g., Burnette et al., 2022; Canning & Limeri, 2023). Two crucial motivational beliefs associated with a growth mindset are mastery goals (Blackwell et al., 2007; Burnette et al., 2013; Dupeyrat & Mariné, 2005; Parada & Verlhiac, 2022) and positive effort beliefs (Blackwell et al., 2007; Dweck & Yeager, 2019; Tempelaar et al., 2015). Studies have shown that a growth mindset fosters the adoption of mastery-oriented goals, which in turn lead to greater motivation, effort expenditure, and achievement (Burnette et al., 2013; Dupeyrat & Mariné, 2005; Parada & Verlhiac, 2022). Similarly, a growth mindset can foster positive effort beliefs or a positive attitude towards effort, cascading into proactive learning strategies and challenge-seeking tendencies (Dweck & Yeager, 2019; Qin et al., 2021; Rege et al., 2021; Tempelaar et al., 2015). Hence, when learners adopt a growth mindset, they also see challenges as opportunities to learn and view the exertion of effort as positive.

1.1.3 Direct effects

Focusing on the behavioral indicators of a growth mindset, the IGSF detail six overt and covert behavioral learning strategies (see Table 1). Echoing growth mindset models that feature behavioral indicators (see Yan & Schuetze, 2023), the framework includes positive strategies, perseverance, and proactive coping as behavioral mediators (e.g., planning, instrumental support-seeking, reframing; Bettinger et al., 2018; Blackwell et al., 2007; Lam & Zhou, 2020; Parada & Verlhiac, 2022). Additionally, the IGSF includes cognitive strategies such as metacognitive learning strategies, challenge-seeking, and self-regulated learning as indicators of a growth mindset. Metacognitive strategies include planning, monitoring, adjusting, seeking help, practicing, and generating new problem-solving techniques (Chen et al., 2020). Further, challenge-seeking tendencies, characterized by a preference for difficult academic tasks, have also emerged as a key behavioral indicator of a growth mindset (Bettinger et al., 2018; Qin et al., 2021; Rege et al., 2021; Yeager et al., 2016). Finally, self-regulated learning practices (e.g., effort regulation, goal-setting, strategy knowledge) have also been found to be predicted by growth mindset (Bai & Wang, 2020; Bai et al., 2021; Karlen et al., 2021; Yan et al., 2014). These behavioral indicators (see Table 1) provide a broader understanding of how growth mindset manifests in concrete learning practices, underscoring the dynamic interplay between belief and behavior in learning.

Although distinct in their conceptualization, these behavioral indicators may operate in synergy, with some strategies driving initial engagement, while others are promote sustained effort and adaptation in the face of challenges. We labeled these proactive and reflective growth practices. Proactive growth practices encompass strategies that students use to initiate and regulate their learning. It includes positive strategies, challenge-seeking, and self-regulated learning (Bai & Wang, 2020; Bettinger et al., 2018; Blackwell et al., 2007). These practices represent initiative-taking

Table 1 Behaviors that demonstrate the effect of growth mindset

Behaviors	Conceptual definition	Operational definition/sample behaviors	Reference
(1) Positive strategies	Positive effort-based learning strategies	Working harder; spending longer study time	Blackwell et al. (2007)
(2) Self-regulated learning	Self-regulated learning involves being an active, engaged, and metacognitively aware learner who plans, monitors, controls, and adapts their learning process using effective strategies	Utilizes effective study strategies like spaced study, self-testing, and metacognitive monitoring; adapts and discerns study techniques based on self-assessment; aims to master material beyond just scoring well; actively revises work based on feedback; and engages in regular study practice beyond assignments	Yan et al. (2014); Bai et al. (2021)
(3) Preference for challenging tasks	Students' motivation and willingness to choose demanding, difficult tasks that will improve their abilities and promote learning, even if it means risking poorer performance or struggling	Choosing more very challenging problems despite having easier alternatives. That is, choosing tasks described as challenging where they could learn something new over one described as easy with problems they can do without much thinking	Rege et al. (2021); Qin et al. (2021)
(4) Proactive coping	Cognitive-behavioral strategies where one anticipates and frames potential challenges as opportunities for growth, reinterpreting stressful situations as challenges instead of threats, thereby fostering positive motivation, effective stress management, and a proactive approach to difficulties	Takes proactive measures to address situations; actively strategizes in response to challenges; seeks external guidance and advice when needed; identifies positive aspects in current circumstances	Parada & Verlhiac (2022) (see also, Greenglass, 2002)

Table 1 (continued)

Behaviors	Conceptual definition	Operational definition/sample behaviors	Reference
(5) Metacognitive learning strategies	Actively analyzing tasks and then planning, self-monitoring, and revising strategies for challenging goals	Strategically plans steps for desired academic outcomes; monitors the effectiveness of learning methods; adapts strategies when noticing limited progress; reflects on learning approaches to identify strengths and weaknesses	Chen et al. (2020)
(6) Perseverance	Sustained and consistent effort, particularly in challenging contexts, characterized by an unwavering focus, dedication to rewarding tasks, and a relentless commitment to long-term goals despite adversity	More focused and effortful on tasks; efficient despite increasing task difficulty; spends time on challenging tasks (not giving up easily); completing tasks; diligent	Bettinger et al. (2018); Lam & Zhou (2020) (see also Duckworth & Quinn, 2009)

behaviors that students engage in to enhance their learning and growth. These practices represent initiative-taking behaviors that help students plan, structure, and direct their learning before engaging in learning tasks. Self-regulated learning, in this context, involves goal-setting, strategy selection, and effort regulation—all of which are forward-looking processes designed to optimize learning.

Reflective growth practices, on the other hand, come into play when proactive practices are met with challenges. They include perseverance, proactive coping, and metacognitive learning strategies (Chen et al., 2020; Lam & Zhou, 2020; Parada & Verlhiac, 2022). Unlike proactive strategies, these focus on post-task reflection and adjustment, helping students analyze setbacks, refine their approaches, and integrate lessons learned from past experiences. Metacognitive learning strategies specifically involve evaluating the effectiveness of previously used strategies, self-monitoring for errors, and adapting approaches based on feedback. This temporal and functional conceptualization aligns with the dynamic nature of the learning process and the complex ways in which a growth mindset may manifest in learning behaviors (Burnette et al., 2013; Yeager & Dweck, 2020).

In sum, our integrated framework delineates the sequential pathways of how a growth mindset translates to meaningful learning and achievement gains through behavioral mechanisms.[1] This model not only details the intricate processes underpinning the growth mindset-to-achievement link but also lays the theoretical groundwork for the development of an instrument that assesses learning practices associated with a growth mindset.

1.2 Identifying and assessing student behaviors that manifest a growth mindset

Identifying and assessing specific behaviors associated with growth mindset is crucial for several reasons. First, while growth mindset beliefs are implicit, their manifestation in cognitive-behavioral strategies provides a more concrete and actionable understanding of how these beliefs influence learning (Blackwell et al., 2007; Dweck & Yeager, 2019). Second, examining these behaviors allows for the identification of potential incongruences between beliefs and actions (e.g., Barger et al., 2022; Dweck, 2015; Lou et al., 2022; Patrick & Joshi, 2019), addressing the issue of a false growth mindset (Barger et al., 2022; Dweck, 2015). Third, intervening in behaviors could potentially serve as a pathway towards changing beliefs, offering an indirect method to foster growth mindsets (see Albarracín et al., 2024). It is therefore necessary to not only identify but

[1] Of note, while the IGS framework is modeled in temporal directionality, that much of the components can have co-occurring or reciprocal effects. For example, adopting a growth mindset can operate simultaneously with having mastery-oriented goals and positive effort beliefs. In terms of reciprocal effects, it is possible that academic achievement becomes the *context* for subsequent achievement. Similar to current theoretical models, the framework could be viewed from a top-down, bottom-up, or cyclical lens.

also to measure the ensuing behaviors and practices stemming from a growth mindset.

While existing growth mindset measures provide valuable insights, there's a growing need for instruments that capture behavioral manifestations of these beliefs. This need stems from recognizing that mindset interventions may benefit from more specific, actionable targets (Yeager et al., 2019). By focusing on observable behaviors and practices, we can bridge the gap between abstract beliefs and concrete actions, potentially enhancing intervention effectiveness. Researchers have called for such tailored instruments (Burnette et al., 2022; Yan & Schuetze, 2023), arguing for measures that assess specific behaviors (Chen et al., 2020) or domain-specific practices (Bostwick et al., 2017; Lou & Noels, 2016; Tock et al., 2021). These behavior-focused measures can complement belief-based assessments, providing a more comprehensive understanding of how growth mindset operates in real-world learning contexts.

To reiterate, we conceptualize 'behaviors' in a broad sense, encompassing both observable actions and internal cognitive processes. This includes not only observable actions but also internal cognitive and metacognitive processes that manifest in learning contexts (Pintrich, 2000; Efklides, 2011; Zimmerman, 2002). For instance, while metacognitive strategies like planning or self-reflection may not be directly observable, they represent active, controllable processes that students engage in and are thus considered behaviors in our framework (Chen et al., 2020; Veenman et al., 2006). We refer to these behaviors in the context of growth mindset as *growth practices*. As delineated in the IGSF, these practices manifest as specific learning behaviors encompassing positive strategies, effort, proactive coping, deep and metacognitive learning strategies, challenge-seeking, and self-regulated learning (Bai & Wang, 2020; Bai et al., 2021; Bettinger et al., 2018; Blackwell et al., 2007; Chen et al., 2020; Karlen et al., 2021; Lam & Zhou, 2020; Parada & Verlhiac, 2022; Qin et al., 2021; Rege et al., 2021; Yan et al., 2014; Yeager et al., 2016).

Collectively, growth practices are effort-based learning behaviors and strategies focused on learning and improvement. These actionable practices are goal-directed, mastery-oriented, and formative—they involve iterative feedback processes, where students continually adjust their strategies based on the outcomes of their efforts and incorporate new information to refine their learning approaches (e.g., Nicol & Macfarlane-Dick, 2006; Yan & Brown, 2017). Although the definitions of each of the specific practices are relatively distinct, there is a noticeable overlap with their operative definitions. More so, while these behaviors have been examined separately, students likely engage in learning strategies either concurrently or sequentially (see Duncan & McKeachie, 2005; Pintrich, 2003) in the same way that students can adopt multiple goals (Kim et al., 2023). Hence, it can be posited that these behaviors can collectively reflect and embody growth mindset beliefs. The nuanced nature of growth practices, encompassing multiple concurrent and sequential behaviors, further underscores the need to assess growth practices.

1.3 The present study

Informed by the IGSF, this study aims to develop and validate the Growth Practices Scale (GPS), an instrument assessing students' learning behaviors that manifests and reflects a growth mindset. While existing measures focus primarily on beliefs, the GPS captures student's effort-based learning strategies and practices, addressing several key issues in the field. The GPS is designed to complement, not replace, existing belief measures (Burnette et al., 2022; Macnamara & Burgoyne, 2022) by capturing how growth mindset operates in real-world learning contexts. Guided by our integrated framework, we sought to identify and assess these key behavioral practices. Cross-sectional and longitudinal data was collected from undergraduate students to test the scale's dimensionality and reliability, as well as its nomological, incremental, and temporal validity (i.e., test–retest reliability, within-person longitudinal measurement invariance).

2 Methods

2.1 Scale development

The development of the Growth practices scale (GPS) was based on the review of existing literature, focus group discussion, expert review, and pilot-testing. Specifically, the iterative item development process combined top-down (derived from the Integrated Growth Systems Framework, IGSF) and bottom-up (informed by focus groups) approaches. The final steps involved content validation by an expert panel and pilot testing through cognitive interviews.

2.1.1 Initial item generation

Items were first drawn from a review of empirical studies on behavioral indicators of growth mindset. This review was guided by the Integrated Growth Systems Framework (IGSF), which synthesizes current theoretical understanding and empirical findings in the field of growth mindset research. An initial set of 21 items was generated based on this review. We paid particular attention to learning strategies that have been empirically linked to academic achievement in previous studies. For instance, we drew from empirical studies that identified specific behaviors associated with a growth mindset (e.g., actively strategizes in response to challenges; Parada & Verlhiac, 2022) and theoretical papers proposing key manifestations of growth mindset in academic settings (e.g., preference for challenging tasks; Dweck & Yeager, 2019). To ensure content validity, we included items that represented both cognitive (e.g., "*I view challenges as opportunities to learn*") and behavioral manifestations (e.g., "*I create a study schedule to do* *better on tests*") of each component. We also aimed to capture behaviors across different academic contexts, from classroom learning to independent study.

2.1.2 Focus group discussion

Second, we conducted online focus group discussions with four groups of undergraduate students, each group with three to five participants. To have a unified understanding of what a growth mindset is, the FGD started with an introduction to the concept of growth mindset, including its definition and its impact on student learning. The rationale for providing this introduction was to ensure all participants had a common baseline understanding of growth mindset. While this approach might have influenced participants' responses to some degree, we believed it was necessary to facilitate meaningful discussions about growth mindset behaviors. This reconciled varying or potentially inaccurate notions that participants might have had of growth mindset. The discussion was focused on answering the question: "What does a student with a growth mindset—that could be you or someone you know—do in class to enhance learning?" This open-ended question allowed participants to draw from their own experiences and observations, even if they had just learned about the concept. Consequently, the responses were analyzed and coded, with an aim to add new items and refine and/or replace unclear or overlapping items from the initial pool. Some themes included, "*I think students with a growth mindset always look for the silver lining, even in failures. They see them as opportunities to learn and improve.*", "*They don't give up easily. Even when things get tough, they keep pushing through because they believe they can improve.*", and "*They're always reflecting on their studies, asking themselves what worked well and what didn't, and adjusting their approach accordingly.*" Although no new items were added, the FGDs made the items more specific to higher education and replaced repetitive or overly similar items. This process led to 17 refined items.

2.1.3 Expert panel review

The refined item pool was then reviewed by an expert panel consisting of three educational researchers, one educational psychologist, and two licensed psychometricians. Although the panel has substantive expertise on the concept of growth mindset, they were provided with the theoretical and operational definition and description of growth mindsets to ensure consistency in their evaluation of the items. The expert panel then: (a) reviewed whether the items reflected the concept of growth practices (b) rated how essential each of the items was to capture the overall construct on a scale ranging from "essential," "useful, but not essential," to "not necessary." Items are assessed for having a positive content validity ratio (CVR, i.e., four or more experts rating essential; see Almanasreh et al., 2022). The panel also commented on the wording and specificity of the items. Five items were excluded in this process for having negative CVRs. The final item pool, which contained a total of 12 items, can be found in Table 2. The items for the GPS cover self-directed behaviors aimed at improvement which covers goal-setting, deliberate preparation, seeking challenges, among others. There were also items focused on adaptability to

Table 2 Exploratory factor analysis of GPS items (N = 575)

GPS items	F1	F2	IGSF taxonomy
GPS1. I actively seek out opportunities to improve my performance in school	0.61	0.09	Positive strategies [*agentic engagement*]
GPS2. I search for relevant and credible sources of information to support my learning (e.g., academic journals, credible online resources, and teachers)	0.52	0.08	Self-regulated learning [*information-seeking*]
GPS3. I set specific learning goals, such as earning a certain grade or mastering a particular skill, to improve my academic performance	0.75	0.02	Self-regulated learning [*goal setting*]
GPS4. I create a study schedule and stick to it to do well on tests or assignments	0.66	0.00	Self-regulated learning [*deliberate preparation*]
GPS5. I exert my best effort to ensure that my assignments are of high quality	0.54	0.12	Positive strategies [*effort regulation*]
GPS6. I seek out academic challenges to develop my academic abilities (e.g., enrolling in advanced courses, engaging in research activities)	0.74	–0.11	Preference for challenging tasks [*challenge-seeking*]
GPS7. When I receive poor results on my assignments or tests, I ask for feedback on how to improve and apply them to future work	0.29	0.38	Proactive coping [*feedback-seeking*]
GPS8. I reflect on the mistakes I make so I can adjust my study habits accordingly to improve	–0.02	0.79	Metacognitive learning strategies [*self-reflection*]
GPS9. I give myself credit for the effort I put into my academic pursuits, even if I fail or do not achieve my desired outcome	–0.08	0.65	Proactive coping [*positive effort attribution*]
GPS10. I turn academic challenges into learning opportunities by viewing them as necessary steps to improve	0.04	0.79	Metacognitive learning strategies [*reframing*]
GPS11. I explore alternative strategies and keep going when I encounter academic difficulties (e.g., struggling with a concept or failing an assignment)	0.12	0.60	Perseverance [*adaptability*]
GPS12. I easily bounce back after experiencing academic challenges or failure	0.18	0.13	Perseverance [*resilience*]

challenges, such as feedback-seeking, self-reflection, positive effort-attribution, and reframing. Given that the items were learning strategies, the response options were based on the frequency of behavior where participants rate how often they engage in each item on a 5-point Likert scale from 1 (*rarely* or *never*) to 5 (*almost always* or *always*). Higher scores reflect greater engagement in growth practices.

2.1.4 Pilot testing

The final item pool was pilot-tested with six men and six women (aged 18 to 22 years, from different majors) through online cognitive interviews. Cognitive interviews provide critical validity evidence by assessing how participants interpret and respond to scale items (Castillo-Díaz & Padilla, 2013). Participants verbalized their thought processes while answering each item, allowing us to identify potential ambiguities and ensure the items accurately captured the intended growth mindset behaviors. Minor adjustments were made to item wording, sequence, and instructions based on this feedback, ensuring relevance across academic domains. The cognitive interviewing process provided valuable insights into the response processes, strengthening the construct validity of the Growth practices scale (GPS) and confirming that participants understood the items as intended (see Willis et al., 2011).

2.2 Participants and procedures

A total of 1,150 undergraduate students from a large higher education institution in the Philippines participated in this study. The college, located in Pampanga, which is a two-hour drive from the capital, Manila, offers a range of programs, including business, education, information technology, and hospitality management, among others. This diverse academic context provides a rich environment for studying growth mindset practices across different fields of study in higher education. Participants were recruited from various academic programs, representing a diverse range of disciplines within the institution. The survey was administered in English, which is commonly used in higher education settings in the Philippines. Data was collected using Qualtrics, an online survey platform, ensuring standardized administration and ease of access for participants.

The sample was predominantly female (70.61%), with a mean age of 20.52 years ($SD = 1.99$). The majority of the participants were first-year students (36.52%), followed by second year (27.57%), with the remaining participants distributed across upper years. This distribution allows for a representation of students at different levels of their academic courses, potentially capturing varying levels of experience with growth-oriented practices.

Informed consent was obtained from all participants, and the study received ethics approval from the institutional review board of the participating institution. A follow-up data collection was conducted two months after the initial survey to evaluate the temporal stability of the Growth practices scale (GPS), this second phase involved 575 students from the original sample.

2.3 Validation study measures

Growth practices scale (GPS). The GPS is the newly developed self-report instrument designed to assess students' growth practices, capturing learning strategies that demonstrate their growth mindset. The scale development process is detailed in Sect. 2.1. A similar approach has also been adopted in assessing growth-oriented pedagogies or teaching practices for teachers (e.g., Canning et al., 2022; Kroeper et al., 2022a, 2022b; Kroeper, Muenks, et al., 2022; Muenks et al., 2020). The final version consists of 12 items (see Table 2). In the study, the GPS demonstrated good internal consistency reliability (α = 0.88). See supplementary files, for the GPS-11 (Supp 1) and its adaptable version (Supp 2).

To establish the criterion-related and incremental validity of the GPS, we included the following established measures:

Motivated learning strategies. Four items from the Motivated Strategies for Learning Questionnaire (MLSQ; Duncan & McKeachie, 2005; Pintrich et al., 1993) were used. This construct aligns with Dweck and Leggett's, (1988) theory that growth mindset leads to learning-oriented responses, including a preference for challenging tasks (see also Qin et al., 2021). The items are: (1) I prefer course materials that really challenge me so I can learn new things; (2) I prefer course material that arouses my curiosity, even if it is difficult to learn; (3) the most satisfying thing for me is trying to understand the course content as thoroughly as possible; and (4) When I have the opportunity, I choose course assignments that I can learn from even if they don't guarantee a good grade. The items were responded on a seven-point Likert scale from *not at all true of me* to *very true of me*. The internal reliability of the subscale in this study was α = 0.88.

Mastery approach goals. Three items representing mastery approach goals were used from the Achievement goal questionnaire-revised (AGQ-R; Elliot & Murayama, 2008). Burnette et al., (2013) meta-analysis found that growth mindset is positively associated with learning goals, making the mastery approach a relevant criterion-related construct. The items are: (1) My aim is to completely master the material presented in this class; (2) I am striving to understand the content of this course as thoroughly as possible; and (3) My goal is to learn as much as possible. These were responded to on the same seven-point scale as the MLSQ. The internal reliability of the subscale in this study was α = 0.86.

Academic resilience. Five items from the School Resilience Scale (SRS; Caleon & King, 2021) were used to assess academic resilience. Yeager and Dweck, (2012) posit that a growth mindset fosters resilience in academic settings. These items are: (1) I can recover quickly after experiencing setbacks in school (e.g., bad marks, negative comments on schoolwork); (2) I am good at coping with problems related to schoolwork; (3) I can manage stress in schoolwork easily; (4) I don't let difficulties in schoolwork affect my confidence; (5) After experiencing setbacks (e.g., bad marks, negative comments on schoolwork), I can do much better in school if I put my mind into it. The items were responded to on a seven-point scale from *strongly disagree* to *strongly agree*. The internal reliability of the subscale in this study was $\alpha = 0.91$.

Growth mindset. To establish incremental validity, we included the Incremental Beliefs subscale of the Implicit Theories of Intelligence Self-theory scale (De Castella & Byrne, 2015). We included a measure of growth mindset beliefs to examine how the growth practices scale predicts achievement while controlling for growth mindset. The growth mindset subscale consists of four items: (1) With enough time and effort I think I could significantly improve my intelligence level; (2) I believe I can always substantially improve my intelligence; (3) Regardless of my current intelligence level, I think I have the capacity to change it quite a bit; and (4) I believe I have the ability to change my basic intelligence level considerably over time. The items were responded to with a six-point scale, ranging from *strongly disagree* to *strongly agree*. The internal consistency of the subscale in this study is $\alpha = 0.85$.

Academic achievement. To test the incremental validity of the GPS, we collected participants' self-reported grade point average (GPA) for the midterm period of the semester as a measure of achievement. Scores ranged from 75 to 98.5 ($M = 91.61$; $SD = 3.03$).

2.4 Data analysis

The data analysis was conducted in four stages. First, to examine the within-network validity of the GPS, we incorporated exploratory graph analysis (EGA) and exploratory factor analysis (EFA) to test its dimensionality, then further tested its factor structure through the integration of confirmatory factor analysis (CFA) and multidimensional Rasch analysis. This stage also included the evaluation of internal reliability. Second, for between-network validity, structural equation model (SEM) was used to test the nomological validity of the GPS. In the third stage, we tested the within-person longitudinal invariance of the GPS and examined its test–retest reliability to examine temporal validity and stability. Finally, we used a multiple regression analysis to test the incremental validity of the GPS.

For the within-network validity, the dataset was randomly split into two equal halves. The first half was used for both EGA and EFA. In the EGA, the EGAnet package was used to determine the number of dimensions within the data based on 1000 bootstrap samples (Christensen & Golino, 2021).[2] The number of dimensions detected by the EGA was further validated through an EFA on the same data split. The suitability of the data for factor analysis was evaluated using Bartlett's

[2] The non-parametric (resampling) procedure was implemented in this study. This procedure works by resampling from the original data with replacement (with the same number of cases as the original data). The resampling procedure allows some cases to be represented more than once in a replicate sample, while other cases may not be included. EGA is then applied to the replicate data, continuing iteratively until the desired number of samples is achieved (e.g., 1000). The result is a sampling distribution of EGA networks.

test of sphericity and the Kaiser–Meyer–Olkin measure (KMO). A parallel analysis with scree plots was then conducted to ascertain the number of factors to retain. Following this, factors were extracted using maximum likelihood extraction with an oblique rotation, considering the anticipated correlation between the constructs. The goodness-of-fit of the model was gauged using the Tucker–Lewis Index (TLI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA).

The second half of the sample was used for the CFA and multidimensional Rasch analysis where the two-factor model derived from the exploratory phase was further evaluated. The integration of both analytic procedures has been shown to ensure the robustness of a scale's psychometric properties (Chang & Engelhard, 2016; Testa et al., 2019; Yan, 2020). For the CFA, the fit of the model was assessed using several fit indices such as the Satorra-Bentler scaled chi-square, CFI, TLI, RMSEA, and SRMR. A chi-square difference test was also carried out to contrast the two-factor model with a unidimensional model, supplemented by a comparison of the Akaike Information Criterion and Bayesian Information Criterion values. The Rasch analysis enhances measurement precision by considering intercorrelations between subscales (Bond et al., 2020) and includes indicators such as Rasch reliability, response category functioning, and item MNSQ fit statistics.

For the between-network validity, the nomological validity of the scale was examined through an SEM analysis, which utilized the full dataset. The SEM hypothesized that the GPS factors would predict motivated learning strategies, mastery approach goals, and academic resilience. Several fit indices, including Satorra–Bentler scaled chi-square, CFI, TLI, RMSEA, and SRMR, were used to assess the fit of the model. All potential paths were tested for statistical significance, and the covariance among the factors was also evaluated.

In examining the temporal validity and stability of the GPS, we tested its configural, metric, scalar, and residual (strict) within-person longitudinal measurement invariance. An SEM was used to assess the fit of the two-factor model and was tested following a progressive model-constraint approach. This method starts with the least restrictive model (configural invariance), progressively introduces constraints (metric, scalar, and residual invariance), and evaluates the difference in model fit. Given the within-person variability of the data, we followed (Mackinnon et al., 2022) in terms of the sets of parameters that were constrained, which includes covarying item intercepts for each model. The same fit indices in the factor analyses were used to evaluate the overall model fit. A difference in CFI (ΔCFI) smaller than or equal to 0.01, alongside ΔRMSEA and ΔSRMR less than or equal to 0.015 and 0.01, respectively, was considered as evidence of invariance (Chen, 2007). In cases where invariance criteria were not met, consideration was given to the relative fit of the model, the sample size, and the robustness of the scale, as these factors can affect the stringency of measurement invariance tests (Marsh et al., 2004; Meade et al., 2008).

Consequently, we conducted a multiple regression analysis to test the incremental validity of growth practices in predicting achievement. The model included proactive and reflective growth practices as predictors while controlling for growth mindset beliefs, socioeconomic status (SES), sex, and age. This approach allowed us to

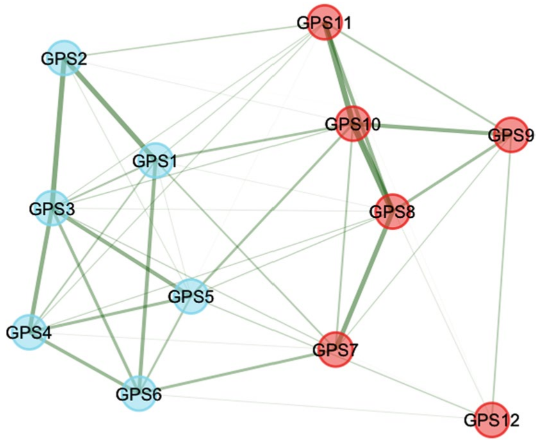

Fig. 2 Exploratory Graph Analysis (EGA) network visualization of the Growth Practices Scale items
Note: Nodes represent individual scale items, and edges represent partial correlations between items. Node colors indicate community membership, with blue nodes (GPS1-GPS6) representing proactive growth practices and red nodes (GPS7-GPS12) representing reflective growth practices. Edge thickness indicates the strength of relationships between items

determine whether engagement in growth-oriented learning behaviors uniquely contributes to academic achievement beyond known predictors and covariates.

A test–retest reliability was evaluated using the longitudinal data in an SEM framework. All items were considered to load on their respective latent factors in Time 1 and Time 2, with no items allowed to covary. This allows us to account for item-level measurement errors. We then examined how the factors in Time 1 predicted the corresponding factors in Time 2. Model fit was assessed using various fit indices that were also examined in previous models. Apart from the Rasch analysis, which was run in ConQuest 2.0 (Wu et al., 2007), all other analyses were conducted through the statistics software R (R Core Team, 2016).

3 Results

3.1 Within-network validity

3.1.1 Exploratory graph analysis

The exploratory graph analysis (EGA) was based on 1000 bootstrap samples of the first random split of the sample (n = 575). The median number of dimensions (i.e., clusters of highly interrelated items, often referred to as communities) identified was two (SE = 0.53), with a 95% confidence interval ranging from 0.96 to 3.04. This estimate was supported by the data, as evidenced by a bootstrap frequency of 0.602 for two dimensions, compared to frequencies of 0.371 for one dimension and 0.027 for three dimensions. The EGA identified two communities of items within the dataset (see Fig. 2). The first community comprised items GPS1 to GPS6, while the second community comprised items GPS7 to GPS12.[3] This structure is consistent with the median number of dimensions identified, providing an empirical foundation for the presumed dimensionality of the dataset, and supporting the interpretation of the two dimensions as distinct constructs.

3.1.2 Exploratory factor analysis

Using the same sample from the EGA, an exploratory factor analysis (EFA) was conducted to assess the underlying factor structure of the GPS. Prior to conducting the EFA, the suitability of the data for factor analysis was assessed. Bartlett's test of sphericity was statistically significant ($\chi^2(66) = 2466.728$, $p < 0.001$), indicating that the data was suitable for factor analysis. Additionally, the KMO measure verified the sampling adequacy for the analysis, KMO = 0.92, suggesting a high degree of common variance among items. Each item also showed sufficient individual sampling adequacy, ranging from 0.90 to 0.94. A parallel analysis with scree plots suggested a two-factor model.

Consequently, the EFA considering these two factors was carried out using maximum likelihood extraction with an oblique rotation, allowing both factors to correlate. The goodness-of-fit indices suggested an acceptable model fit: TLI = 0.967, CFI = 0.979, and RMSEA = 0.045, suggesting that the model adequately explained the data. The two factors accounted for 44% of the variance. Factor 1 explained 24% of the variance, and Factor 2 explained an additional 20%. The loading matrix (see Table 2), with standardized loadings based upon the correlation matrix, showed that items GPS1 to GPS6 had strong loadings (ranging from 0.52 to 0.75) on Factor 1, whereas items GPS7[4] to GPS11 exhibited substantial loadings (ranging from 0.38 to 0.79) on Factor 2. Moreover, the factor correlation was 0.74, demonstrating a moderate relationship between the two factors. Given the item statements that loaded on the factors, factor 1 is conceptualized as "proactive growth practices" and factor 2 is conceptualized as "reflective growth practices". Aligned with the EGA results, GPS12 loaded low on both factors and is therefore removed from the subsequent confirmatory factor analysis (CFA). The 11-item GPS had an internal reliability rating of $\alpha = 0.88$, with its two subscales both having the same reliability ($\alpha = 0.82$).

[3] Footnote: While GPS12 "I easily bounce back after experiencing academic challenges or failure." was included in the second dimension, the connections of GPS12 with other items in the second dimension appear to be relatively weak, as evidenced by the weaker edge weights in the graphical representation. This weaker connection may suggest that GPS12's relationship with the rest of the items in the factor is not as robust as that of other items.

[4] Footnote. The GPS 7 "When I receive poor results of my assignments or tests, I ask for feedback on how to improve and apply them to future work" loaded on both factor 1 (0.29) and factor 2 (0.38). Given the theoretical relevance of the item, we did not delete this item and instead empirically tested which factor the item can be best assigned to. We assigned it to factor 2 informed by the results of the EGA and the internal consistency rating of adding/dropping the item from each factor.

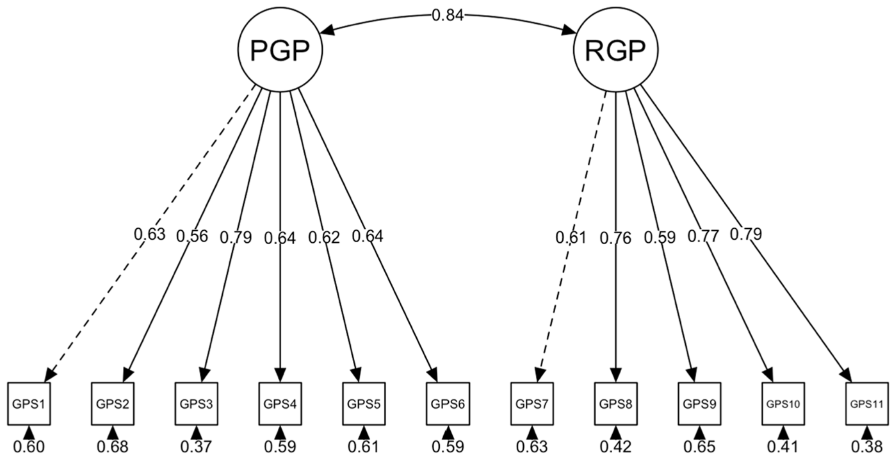

Fig. 3 The two-factor structure of the GPS, with proactive growth practices (PGP) and reflective growth practices (RGP)

3.1.3 Confirmatory factor analysis

A two-factor CFA was conducted using the second random split of the sample (n = 575). The model showed a reasonable fit to the data, $SB\chi^2(43) = 118.490$, $p < 0.001$, CFI = 0.952, TLI = 0.939, RMSEA = 0.069 (90% CI = 0.058–0.080), SRMR = 0.035, indicating a good model fit. The six items loaded to proactive growth practices (PGP) had statistically significant factor loadings ranging from 0.61 to 0.86, whereas the five items loaded to reflective growth practices (RGP) had significant factor loadings ranging from 0.64 to 0.80 (see Fig. 3). The covariance between the two factors was 0.84, indicating a high relationship between the two factors. Given the high covariance between PGP and RGP, a chi-square difference test was performed to compare the two-factor model with a unidimensional model where all 11 items are loaded onto a single factor. The test indicated that the two-factor model provided a significantly better fit to the data than the unidimensional model, $\Delta\chi^2(1) = 63.873$, $p < 0.001$. The two-factor model had lower values for both the Akaike Information Criterion (AIC; 16,905 vs. 17,009) and the Bayesian Information Criterion (BIC; 17,053 vs. 17,152), providing further support for the two-factor model.

3.1.4 Rasch analysis

Given that the theorized two-factor model of GPS was supported by the data, a multidimensional Rasch model (Adams et al., 1997) was employed on the full dataset (N = 1150). The results showed that the functioning of the five-point rating scale was satisfactory as the step calibrations (i.e., the measures of the transition points between adjacent categories) increased monotonically from − 1.96, − 0.03, 0.25, to 1.74 logits. The Infit and Outfit MNSQs of most items were within the

Table 3 Item difficulty, item fit statistics, and gender DIF for the 11-item GPS

Item no	Item measure[a]	SE	Infit MNSQ	Outfit MNSQ	Gender DIF[b]
Proactive growth practices (PGP)					
GPS 1	0.05	0.02	1.11	1.09	0.14
GPS 2	−0.49	0.03	1.2	1.19	0.08
GPS 3	−0.10	0.03	0.79	0.78	0.05
GPS 4	0.23	0.02	1.14	1.15	0.26
GPS 5	−0.51	0.03	0.89	0.91	0.17
GPS 6	0.83	0.06	1.19	1.17	0.32
Reflective growth practices (RGP)					
GPS 7	0.87	0.03	1.21	1.21	0.05
GPS 8	−0.42	0.03	0.83	0.79	0.01
GPS 9	−0.16	0.03	1.17	1.14	0.05
GPS 10	−0.33	0.03	0.71	0.68	0.09
GPS 11	0.04	0.05	0.8	0.82	0.10

[a]All measures are in logits. [b]The figures for gender DIF represent the absolute values (in logits) of the differences in item difficulty between males and females

recommended range (0.75–1.33), indicating a sufficient fit to the Rasch model (Wilson, 2005). Item GPS10 (Infit MNSQ = 0.71; Outfit MNSQ = 0.68) was marginally out of the range but still acceptable (Linacre, 2006). There was no item showing Differential Item Functioning (DIF) across gender because the difference in item difficulty between males and females was lower than 0.5 logits for all items. The item difficulty, standard error, item fit statistics, and gender DIF result for each item are presented in Table 3.

3.2 Between-network validity

We also used the full dataset (N = 1150) in an SEM to test the nomological validity of the GPS. The model hypothesized that proactive growth practices (PGP) and reflective growth practices (RGP) would predict motivated learning strategies (MLS), mastery approach goals (MsA), and academic resilience (Rsl) to establish nomological validity (see Fig. 4). Model fit indices were in the acceptable range: $\chi^2(220) = 818.23$, $p < 0.001$, CFI = 0.936, TLI = 0.926, RMSEA = 0.055 [90% CI 0.051, 0.059]), and SRMR = 0.046), indicating that the proposed model fits the data adequately.

Both proactive and reflective growth practices were found to significantly predict motivated learning strategies (PGP: $\beta = 0.31$, $p < 0.001$; RGP: $\beta = 0.44$, $p < 0.001$), mastery approach goals (PGP: $\beta = 0.26$, $p < 0.01$; RGP: $\beta = 0.50$, $p < 0.001$), and academic resilience (PGP: $\beta = 0.19$, $p < 0.05$; RGP: $\beta = 0.29$, $p < 0.001$). These demonstrate the nomological validity of the GPS subscales. In terms of covariance, a significant positive covariance was observed between PGP and RGP ($\beta = 0.82$, $p < 0.001$). Intercorrelations and descriptives are shown in Table 4.

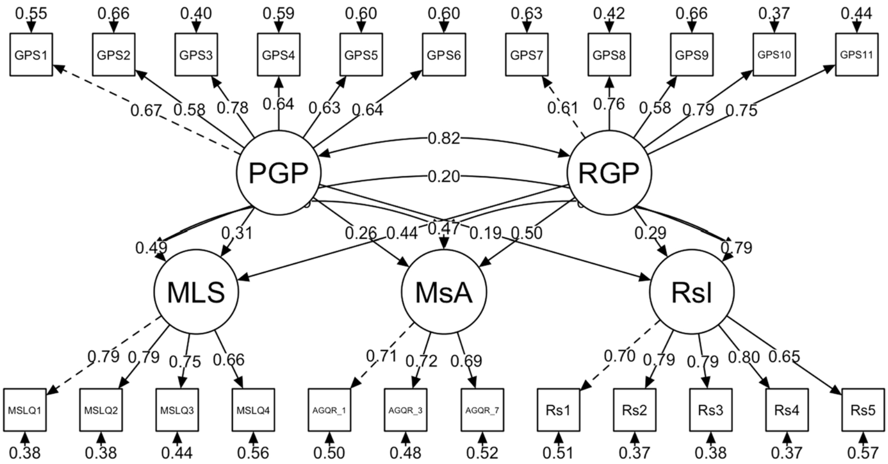

Fig. 4 Structural equation model with GPS factors predicting preference for motivated learning strategies, mastery approach goals, and academic resilience

Table 4 Bivariate correlations, descriptive statistics, and reliability of the variables

Variable	1	2	3	4	5	6	7
1. Growth mindset	(0.90)						
2. Proactive growth practices	0.16^{***}	(0.82)					
3. Reflective growth practices	0.20^{***}	0.68^{***}	(0.82)				
4. Motivated learning strategies	0.23^{***}	0.56^{***}	0.57^{***}	(0.83)			
5. mastery approach goals	0.26^{***}	0.53^{***}	0.55^{***}	0.57^{***}	(0.74)		
6. Academic resilience	0.15^{***}	0.36^{***}	0.39^{***}	0.39^{***}	0.36^{***}	(0.86)	
7. Achievement (grade)	0.15^{***}	0.16^{***}	0.17^{***}	0.09^{**}	0.20^{***}	0.06	–
Mean	5.43	3.55	3.77	4.65	5.47	4.97	91.61
Standard deviation	1.28	0.83	0.81	1.29	1.14	1.18	3.03
Skewness	−1.42	−0.24	−0.55	−0.32	−0.71	−0.64	−0.93
Kurtosis	2.45	−0.62	−0.27	−0.54	0.08	0.19	2.72

$^{***}p > 0.001$. Values shown in parentheses on the diagonal are internal consistency reliabilities of the scales (Cronbach's alpha)

3.3 Incremental validity

A linear regression analysis of 1,150 observations was used to examine the prediction of proactive growth practices, reflective growth practices, growth mindset, and demographic variables on the achievement scores (see Table 5). After controlling for growth mindset, the GPS factors still significantly predicted achievement ($\beta = 0.27$, $p < 0.001$ for proactive growth practices; $\beta = 0.29$, $p < 0.001$ for reflective growth practices), demonstrating incremental validity beyond existing measures of growth mindset. These findings suggest that proactive and reflective growth practices have

Table 5 Multiple regression model with proactive and reflective growth practices predicting achievement scores while controlling for growth mindset and demographics

Variables	β	*SE*	*t*	*p*
Intercept	91.61	0.087	1047.70	< 0.001
Proactive growth practices	0.27	0.12	2.26	0.024
Reflective growth practices	0.29	0.12	2.39	0.017
Growth Mindset	0.35	0.09	3.84	< 0.001
SES	− 0.18	0.09	− 2.05	0.041
Gender	0.05	0.088	0.61	0.545
Age	− 0.09	0.088	− 0.98	0.329

incremental validity in predicting achievement, even after accounting for growth mindset and key demographics.

3.4 Temporal validity and stability

3.4.1 Within-person longitudinal measurement invariance

In testing the GPS' within-person measurement invariance, the error structures that covary item intercepts of the same item in time 1 and time 2 were included (see Fig. 5). This accounts for the within-person variability of the scale as increasing model constraints are introduced to test configural, metric, scalar, and residual invariance. We used longitudinal data that contains a sample of 575, who responded to the GPS twice with a two-month interval. As in Table 6, the configural invariance model (constraining the factor structure across time) provided a good fit, suggesting consistent measurement of the same constructs across time. Similarly, the metric invariance model (constraining all factor loadings across time) showed an acceptable fit.

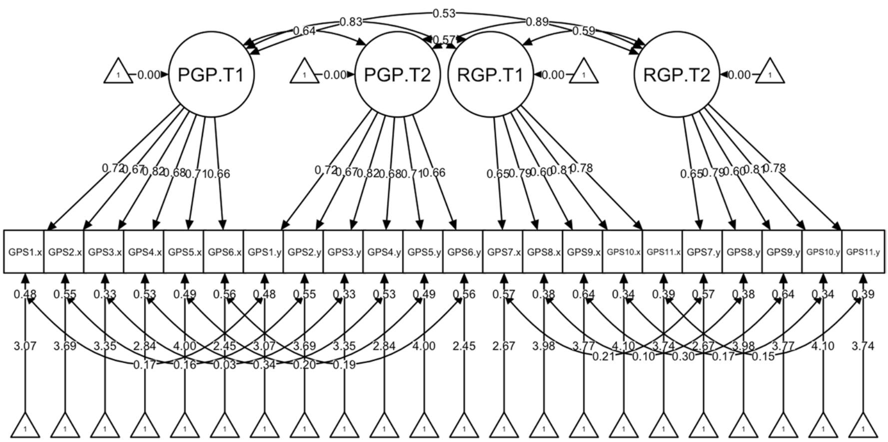

Fig. 5 The plotted residual or strict within-person longitudinal measurement invariance of the two-factor GPS

Table 6 Model fit indices of the GPS, demonstrating longitudinal measurement invariance of the two-factor GPS

Model	SBX^2	df	TLI	CFI	RMSEA	SRMR	ΔCFI	ΔRMSEA	ΔSRMR
1-Factor GPS	195.66	44	0.894	0.916	0.090	0.047	–	–	–
2-Factor GPS	118.49	43	0.946	0.958	0.064	0.035	–	–	–
2-Factor GPS—Configural	407.34	192	0.951	0.960	0.050	0.039	–	–	–
2-Factor GPS—Metric	428.51	203	0.953	0.959	0.050	0.054	0.001	0.000	−0.015
2-Factor GPS—Scalar	552.25	214	0.935	0.940	0.058	0.058	0.019	−0.008	−0.004
2-Factor GPS—Residual	697.00	225	0.914	0.916	0.067	0.055	0.024	−0.009	0.003

Comparing fit indices between the configural and metric invariance models revealed ΔCFI = 0.001, ΔRMSEA = 0.000, and ΔSRMR = −0.015, indicating the invariance of factor loadings over time. The scalar invariance (constraining all item intercepts) also demonstrated acceptable model fit indices. The changes in fit indices from the metric to the scalar invariance model were ΔCFI = 0.019, ΔRMSEA = −0.008, and ΔSRMR = −0.004, which, aside from a marginal decrease in CFI, demonstrates the invariance of item intercepts over time. Finally, residual or strict invariance, which constrains all item errors, was assessed. The residual invariance model exhibited an increase in CFI (ΔCFI = 0.024), exceeding Chen's, (2007) suggested threshold. However, considering the changes in RMSEA (ΔRMSEA = −0.009) and SRMR (ΔSRMR = 0.003) from the scalar to the residual invariance model, we argue that the model fit did not substantially deteriorate. Overall, the results of the longitudinal measurement invariance indicated that the GPS presents excellent goodness of fit for the two-factor model and supports the longitudinal invariance despite the increasing levels of model constraints across time.

3.4.2 Test–retest reliability

A test–retest reliability analysis was conducted using SEM while still using the longitudinal data. The chi-square test indicated a significant discrepancy between the data and the model, $\chi^2(205) = 789.381$, $p < 0.001$. However, chi-square tests are known to be sensitive to large sample sizes, and thus, other fit indices were considered. The model demonstrated a good fit to the data with robust measures, with a CFI of 0.924 and a TLI of 0.914. An acceptable model fit was also indicated by the RMSEA of 0.070 (90% CI [0.065, 0.076]) and the SRMR of 0.043. As with the within-network validity, no items were allowed to covary.

The parameter estimates showed that all items had significant loadings on their respective latent factors ($p < 0.001$). The path from PGP1 to PGP2 was significant, $\beta = 0.66$, $p < 0.001$, indicating good stability for the proactive growth practices measured in Time 1 and Time 2. Similarly, the path from RGP in Time 1 to RGP in Time 2 was significant, $\beta = 0.63$, $p < 0.001$, indicating good stability for the reflective growth practices.

4 Discussion

In lieu of the ongoing critiques on the behavioral mechanisms of the growth mindset-achievement link, this study attempted to advance our understanding of growth mindset processes through two key contributions. Based on the synthesized literature and current theoretical models, the Integrated Growth Systems Framework consolidates and maps the specific behavioral pathways and strategies through which incremental beliefs influence learning. Through comprehensive psychometric validation using longitudinal data, the Growth Practices Scale (GPS) provides a reliable and valid instrument for assessing these behavioral learning strategies. This conceptual and empirical integration can enable researchers to systematically examine how a growth mindset could yield learning gains with enhanced theoretical clarity and measurement precision. Below, we detail these key findings and discuss how future growth mindset research may be informed by the integrated framework and the availability of a valid measure assessing growth practices.

The integrated growth systems framework builds upon the existing literature suggesting that students who adopt a growth mindset tend to engage in positive learning behaviors (Blackwell et al., 2007; Dweck, 2017; Dweck & Leggett, 1988; Dweck & Yeager, 2019; Hong et al., 1999). While our study primarily focuses on developing a measure of these behaviors, it contributes to the ongoing conversation about how growth mindset might enhance academic outcomes (Bostwick et al., 2017; Chen et al., 2020; Dupeyrat & Mariné, 2005; Lam & Zhou, 2020; Parada & Verlhiac, 2022). More specifically, the proposed framework advances the theorizing of the growth mindset by underscoring the specific behaviors (i.e., growth practices) that enable the impact of growth mindset on achievement. These behaviors, as outlined in the framework (Fig. 1), represent how a growth mindset manifests in effort-oriented actions that contribute to learning (Bai & Wang, 2020; Bai et al., 2021; Bettinger et al., 2018; Blackwell et al., 2007; Chen et al., 2020; Karlen et al., 2021; Lam & Zhou, 2020; Parada & Verlhiac, 2022; Rege et al., 2021; Yan et al., 2014; Yeager et al., 2016). With the specification and assessment of these behaviors, our findings initiate crucial steps towards a clearer understanding of the process model to unpack the mechanisms translating mindsets into achievement gains.

Situated in the ecological and systems frameworks (Eccles & Wigfield, 2020; Skinner et al., 2022), the framework conceptualizes beliefs, behaviors, and outcomes within broader contextual predictors. That is, the effectiveness and influence of a growth mindset may vary based on external factors such as cultural background and specific learning environments (Bostwick et al., 2020; Canning & Limeri, 2023; Canning et al., 2022; King, 2019; Lou & Noels, 2019; Zeng et al., 2016). Although our current measure focuses on individual-level factors, we recognize the importance of considering both internal and external factors in growth mindset-related research. Acknowledging learners' contexts and learning environments, although conceptually, underscores the situated and dynamic nature of growth mindset, signifying the importance of accounting for both internal and external factors in growth mindset-related research (Hecht et al., 2023; Muenks et al., 2024).

The Growth practices scale (GPS), guided by empirical studies reviewed in our integrated framework, was developed and validated. Our theoretical framework outlined six categories of growth practices, which we further hypothesized to be grouped into two broader factors. The exploratory graph and factor analyses supported this two-factor structure, which was further confirmed by CFA and Rasch analysis. These two factors are labeled as proactive and reflective growth practices, aligning with our hypothesized second-order categories. The GPS demonstrated excellent psychometric properties, including internal reliability, factor structure, criterion validity, incremental validity, and temporal stability. Specifically, the integration of EGA, EFA, CFA, and Rasch analysis provided robust psychometric testing of the scale's internal reliability, structural validity, and item fit statistics. Further, the SEM supported the scale's nomological validity by positively predicting motivated learning strategies, mastery approach goals, and academic resilience. Incremental validity was also supported by growth practices predicting achievement scores, while accounting for growth mindset. Finally, within-person longitudinal invariance tests and test–retest reliability across a two-month interval further demonstrated the scale's stability over time. Overall, the validity of the scale is supported by progressive empirical tests, establishing a psychometrically sound instrument to assess growth-oriented learning practices.

The proactive growth practices factor reflects learning strategies and responses aimed at self-improvement. This includes exerting effort, setting goals, deliberate preparation, and seeking challenges. These agentic behaviors represent the enactment of a growth mindset through concrete actions beyond just espoused beliefs. The concept of agency is central here, as these practices demonstrate students' capacity to actively shape their learning experiences (see Patall et al., 2022, on agentic mindset). The reflective growth practices factor represents a set of cognitive-behavioral processes that enable resilience when proactive growth practices inevitably result in challenges or setbacks. This includes seeking constructive feedback, analyzing errors for improvement, reframing difficulties as learning opportunities, and persisting despite obstacles (Lam & Zhou, 2020; Yeager & Dweck, 2012). While the first factor captures the overt behaviors of a growth mindset, the second represents the metacognitive skills to sustain those efforts in the face of difficulty (Chen et al., 2020). Seeking challenges often leads to setbacks, which students with growth mindsets can reframe into productive opportunities rather than threats (Burnette et al., 2013). Hence, reflective growth practices potentially follow proactive growth practices. After seeking challenges for mastery, one would need cognitive resources to process feedback, adjust strategies, sustain motivation, and bounce back from inevitable failures that arise. This sequential linkage aligns with recent growth models that position cognitive factors as mediators between mindset and achievement (Yeager et al., 2019).

The GPS reveals both the strategic set of behaviors that embody a growth mindset, and the metacognitive abilities to sustain those behaviors through challenges. This distinction helps articulate a fuller range of processes that could mediate mindset interventions to achievement. Specifying these mechanisms provides further theoretical clarity to the process model of growth mindset and could inform future interventions.

4.1 Theoretical and practical implications

The Integrated Growth Systems Framework, drawn from theoretical models and current empirical research, advances our understanding on how growth mindsets translate into strategic efforts and adaptive responses to challenges. Although the GPS represents a notable step towards understanding and assessing the behavioral underpinnings of a growth mindset, we acknowledge that it does not fully resolve the ambiguities surrounding the process models of growth mindset. Still, it enables researchers to adopt an integrated perspective of whether and how incremental beliefs translate into growth-oriented learning strategies, addressing known incongruences between beliefs and behavior (Barger et al., 2022).

Our empirical findings demonstrate that mindsets manifest in concrete actions beyond mere beliefs (Blackwell et al., 2007; Chen et al., 2020; Yan et al., 2014). The GPS underscores the critical interdependency between beliefs and behaviors in catalyzing achievement-oriented outcomes. While believing in the malleability of abilities represents a necessary foundation, it may be insufficient to drive sustained improvement without accompanying behavioral practices (Macnamara & Burgoyne, 2023; Yan & Schuetze, 2023). Building on the fundamental premise of growth mindset as belief in malleability of abilities (Dweck, 2017; Dweck & Yeager, 2019), a more concrete conceptualization would posit that incremental beliefs enable learners to recognize the substantive gap between their current abilities and their evolving potential. Crucially, to incrementally bridge or close this ability-potential gap requires sustained effort and strategic learning approaches (Bai & Wang, 2020; Burnette et al., 2013).

This theoretical refinement extends beyond generalized beliefs about malleability toward specific mechanisms of developmental progress (Bostwick et al., 2017; Chen et al., 2020). Our framework integrates growth mindset theory with established models of self-regulated learning (Bai et al., 2021; Yan et al., 2021), achievement motivation (Burnette et al., 2013), and academic development (Yeager et al., 2019). This integration emphasizes behavioral enactment as crucial to academic development (Burnette et al., 2022; Dweck & Yeager, 2019). Within this integrated perspective, we define growth practices as “the cognitive-behavioral strategies that reflect a growth mindset—specifically, the sustained efforts and learning approaches through which individuals actively work to close their perceived ability-potential gap.”

Our framework synthesizes previously disparate findings on behavioral mediators into a coherent model centered on specific learning strategies. This theoretical advancement positions the GPS at the intersection of growth mindset, motivation, and self-regulated learning research. By operationalizing key behavioral mechanisms with contextual specificity, the GPS enables generation of testable hypotheses incorporating contextual, cognitive, and behavioral factors, furthering our understanding of mindset-to-achievement pathways and their boundary conditions (Dweck & Yeager, 2019; Yeager et al., 2019).

These theoretical advances have direct implications for mindset interventions. Current mindset interventions, which often yield limited or null long-term effects on achievement (Macnamara & Burgoyne, 2022, 2023; Sisk et al., 2018), may fall short because changed mindsets alone may fail to directly translate into improved achievement without concrete learning behaviors that bridge the two together (Yan & Schuetze, 2023; Yan et al., 2014). Both the integrated framework and the GPS provides a blueprint for bridging this belief-to-behavior gap via concrete growth-oriented practices that interventions can instil or reinforce.

Specifically, the framework identifies actionable targets for intervention, such as reflective growth practices that develop cognitive-behavioral skills (e.g., reframing, positive effort attribution, help-seeking) crucial for resilience after setbacks. The GPS enables formative assessment to tailor interventions and identify specific practices requiring reinforcement, such as effort regulation, deliberate preparation, or feedback-seeking. Moreover, tracking changes in these practices provides direct, proximal indicators of intervention efficacy, allowing for more precise evaluation of growth mindset intervention efficacy.

4.2 Limitations and directions for future research

Despite the strengths of our study, we note several limitations that provide directions for future research. First, while our model provides a deeper understanding of the behavioral mechanisms associated with a growth mindset, our measures primarily focus on individual-level factors and may not fully capture contextual influences. Future research should explore potential moderators and boundary conditions, including how various demographics (e.g., age, gender, socioeconomic status) or contextual factors (e.g., school environment, peer influence) might affect the strength and direction of these relationships. This could provide richer insights into the applicability and generalizability of the integrated framework. Second, although our framework aims to flesh out the sequential link between mindset and achievement, it is possible that the elements (i.e., contexts, beliefs, behaviors, and outcomes) may have direct, cyclical, and reciprocal effects (e.g., Harackiewicz et al., 2008; Schöber et al., 2018; Vu et al., 2022). Future studies could explore these complex interactions to refine our understanding of growth mindset processes. Third, while our data demonstrate associations between growth mindset, growth practices, and achievement, we did not test a full mediation model due to the cross-sectional nature of our data. Future research using longitudinal designs will be crucial for examining the causal pathways implied by our theoretical framework. For instance, studies using cross-lagged panel models could explore the temporal sequencing of mindsets, practices, and achievements over time. Fourth, while self-report measures offer practical advantages, they have inherent limitations in capturing behavioral aspects of growth mindset. To address these limitations, future research could benefit from developing behavioral checklists or incorporating observational measures to complement self-report data. For instance, classroom observations, experience sampling methods, or even physiological measures could provide a more comprehensive assessment of growth practices as they occur in real -time and across various contexts. This multi-method approach would not only validate self-report measures but also capture nuances in growth mindset behaviors that may not be readily accessible through self-reflection alone. Finally, the initial validation of the GPS was limited to undergraduates in an Eastern, non-WEIRD context. Further testing should examine factor structure, invariance, and generalizability across educational levels, achievement domains, and cultural groups. Longitudinal and experimental designs could better establish the temporal and causal relations between GPS factors and outcomes.

4.3 Conclusion

This study advances growth mindset research by providing both theoretical clarity and empirical precision through an integrated examination of learning behaviors and strategies. By systematically mapping and measuring specific growth-oriented practices, our research addresses fundamental questions about how mindset beliefs translate into achievement gains—moving beyond mere belief-outcome associations toward a more nuanced process model. The empirically validated Growth Practices Scale, coupled with our integrated theoretical framework, enables investigation of the complex interplay between beliefs, behaviors, and contextual factors that shape mindset effects. This mechanistic understanding opens critical directions for future research: examining how different educational contexts enable or constrain the expression of growth-oriented practices, investigating individual differences in behavioral manifestation of mindset beliefs, and developing more sophisticated interventions that target both incremental beliefs and specific learning behaviors. Such theoretical and methodological refinement is essential to extend our understanding of how growth mindset operates within broader motivational and cognitive systems to influence educational outcomes. Its limitations notwithstanding, this study forwards a cognitive-behavioral research programme in implicit theories toward nurturing engaged, resilient, and successful learners.

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Declarations

Conflict of interest The authors declare that they have no potential conflict of interest.

References

Abós Catalán, Á., Sevil Serrano, J., Martín-Albo Lucas, J., Julián Clemente, J. A., & García-González, L. (2018). An integrative framework to validate the Need-supportive teaching style scale (NSTSS) in secondary teachers through exploratory structural equation modeling. *Contemporary Educational Psychology, 52*, 48–60. https://doi.org/10.1016/j.cedpsych.2018.01.001

Adams, R. J., Wilson, M., & Wang, W.-C. (1997). The multidimensional random coefficients multinomial logit model. *Applied Psychological Measurement, 21*(1), 1–23. https://doi.org/10.1177/0146621697211001

Almanasreh, E., Moles, R. J., & Chen, T. F. (2022). Chapter 41 - A practical approach to the assessment and quantification of content validity. In S. P. Desselle, V. García-Cárdenas, C. Anderson, P. Aslani, A. M. H. Chen, & T. F. Chen (Eds.), *Contemporary Research Methods in Pharmacy and Health Services* (pp. 583–599). Academic Press. https://doi.org/10.1016/B978-0-323-91888-6.00013-2

Albarracín, D., Fayaz-Farkhad, B., & Granados Samayoa, J. A. (2024). Determinants of behaviour and their efficacy astargets of behavioural change interventions. *Nature Reviews Psychology*. https://doi.org/10.1038/s44159-024-00305-0

Bai, B., & Wang, J. (2020). The role of growth mindset, self-efficacy and intrinsic value in self-regulated learning and English language learning achievements. *Language Teaching Research, 0*(0), 1362168820933190. https://doi.org/10.1177/1362168820933190

Bai, B., Wang, J., & Nie, Y. (2021). Self-efficacy, task values and growth mindset: What has the most predictive power for primary school students' self-regulated learning in English writing and writing competence in an Asian Confucian cultural context? *Cambridge Journal of Education, 51*(1), 65–84. https://doi.org/10.1080/0305764X.2020.1778639

Barger, M. M., Xiong, Y., & Ferster, A. E. (2022). Identifying false growth mindsets in adults and implications for mathematics motivation. *Contemporary Educational Psychology, 70*, 102079. https://doi.org/10.1016/j.cedpsych.2022.102079

Bernardo, A. B. I. (2022). Growth mindset and reading proficiency of ESL learners: Examining the role of students' socioeconomic status using PISA 2018 Philippine data. *European Journal of Psychology of Education*. https://doi.org/10.1007/s10212-022-00629-6

Bernardo, A. B. I., Cai, Y., & King, R. B. (2021). Society-level social axiom moderates the association between growth mindset and achievement across cultures. *British Journal of Educational Psychology, 91*(4), e12411. https://doi.org/10.1111/bjep.12411

Bettinger, E., Ludvigsen, S., Rege, M., Solli, I. F., & Yeager, D. (2018). Increasing perseverance in math: Evidence from a field experiment in Norway. *Journal of Economic Behavior & Organization, 146*, 1–15. https://doi.org/10.1016/j.jebo.2017.11.032

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child Development, 78*(1), 246–263. https://doi.org/10.1111/j.1467-8624.2007.00995.x

Bond, T. G., Yan, Z., & Heene, M. (2020). *Applying the Rasch Model: Fundamental Measurement in the Human Sciences* (4th ed.). Routledge. https://doi.org/10.4324/9780429030499

Bostwick, K. C. P., Collie, R. J., Martin, A. J., & Durksen, T. L. (2017). Students' growth mindsets, goals, and academic outcomes in mathematics. *Zeitschrift Für Psychologie, 225*(2), 107–116. https://doi.org/10.1027/2151-2604/a000287

Bostwick, K. C. P., Collie, R. J., Martin, A. J., & Durksen, T. L. (2020). Teacher, classroom, and student growth orientation in mathematics: A multilevel examination of growth goals, growth mindset, engagement, and achievement. *Teaching and Teacher Education, 94*, 103100. https://doi.org/10.1016/j.tate.2020.103100

Brooks, R., Brooks, S., & Goldstein, S. (2012). The power of mindsets: Nurturing engagement, motivation, and resilience in students. In *Handbook of research on student engagement* (pp. 541–562). Springer.

Burgoyne, A. P., Hambrick, D. Z., & Macnamara, B. N. (2020). How firm are the foundations of mindset theory? The claims appear stronger than the evidence. *Psychological Science, 31*(3), 258–267. https://doi.org/10.1177/0956797619897588

Burnette, J. L., Knouse, L. E., Vavra, D. T., O'Boyle, E., & Brooks, M. A. (2020). Growth mindsets and psychological distress: A meta-analysis. *Clinical Psychology Review, 77*, 101816. https://doi.org/10.1016/j.cpr.2020.101816

Burnette, J. L., Billingsley, J., Banks, G. C., Knouse, L. E., Hoyt, C. L., Pollack, J. M., & Simon, S. (2022). A systematic review and meta-analysis of growth mindset interventions: For whom, how, and why might such interventions work? *Psychological Bulletin, No Pagination Specified-No Pagination Specified.* https://doi.org/10.1037/bul0000368

Burnette, J. L., O'Boyle, E. H., VanEpps, E. M., Pollack, J. M., & Finkel, E. J. (2013). Mind-sets matter: A meta-analytic review of implicit theories and self-regulation. *Psychological Bulletin, 139*, 655–701. https://doi.org/10.1037/a0029531

Cai, J., Wen, Q., Qi, Z., & Lombaerts, K. (2023). Identifying core features and barriers in the actualization of growth mindset pedagogy in classrooms. *Social Psychology of Education, 26*(2), 485–507. https://doi.org/10.1007/s11218-022-09755-x

Caleon, I. S., & King, R. B. (2021). Examining the phenomenon of resilience in schools: Development, validation, and application of the school resilience scale. *European Journal of Psychological Assessment, 37*(1), 52–64. https://doi.org/10.1027/1015-5759/a000572

Canning, E. A., & Limeri, L. B. (2023). Theoretical and methodological directions in mindset intervention research. *Social and Personality Psychology Compass, 17*(6), e12758. https://doi.org/10.1111/spc3.12758

Canning, E. A., Ozier, E., Williams, H. E., AlRasheed, R., & Murphy, M. C. (2022). Professors Who signal a fixed mindset about ability undermine women's performance in STEM. *Social Psychological and Personality Science, 13*(5), 927–937.

Castillo-Díaz, M., & Padilla, J.-L. (2013). How cognitive interviewing can provide validity evidence of the response processes to scale items. *Social Indicators Research, 114*(3), 963–975. https://doi.org/10.1007/s11205-012-0184-8

Chang, M.-L., & Engelhard, G. (2016). Examining the teachers' sense of efficacy scale at the item level with Rasch measurement model. *Journal of Psychoeducational Assessment, 34*(2), 177–191. https://doi.org/10.1177/0734282915593835

Chen, C., Shen, T., Tang, S., Gao, Y., & Wang, D. (2024). Personal belief in a just world and the growth mindset in Chinese adolescence: Prospective between-person and within-person associations. *Applied Research in Quality of Life*. https://doi.org/10.1007/s11482-024-10339-4

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Chen, P., Powers, J. T., Katragadda, K. R., Cohen, G. L., & Dweck, C. S. (2020). A strategic mindset: An orientation toward strategic behavior during goal pursuit. *Proceedings of the National Academy of Sciences, 117*(25), 14066–14072. https://doi.org/10.1073/pnas.2002529117

Chiu, C. Y., Hong, Y. Y., & Dweck, C. S. (1997). Lay dispositionism and implicit theories of personality. *Journal of Personality and Social Psychology, 73*(1), 19–30.

Christensen, A. P., & Golino, H. (2021). Estimating the stability of psychological dimensions via bootstrap exploratory graph analysis: A Monte Carlo simulation and tutorial. *Psych, 3*(3), 479–500.

Dawson, P., Yan, Z., Lipnevich, A., Tai, J., Boud, D., & Mahoney, P. (2023). Measuring what learners do in feedback: the feedback literacy behaviour scale. *Assessment & Evaluation in Higher Education,* 1–15. https://doi.org/10.1080/02602938.2023.2240983

De Castella, K., & Byrne, D. (2015). My intelligence may be more malleable than yours: The revised implicit theories of intelligence (self-theory) scale is a better predictor of achievement, motivation, and student disengagement. *European Journal of Psychology of Education, 30*(3), 245–267. https://doi.org/10.1007/s10212-015-0244-y

Duckworth, A. L., & Quinn, P. D. (2009). Development and validation of the Short Grit Scale (GRIT–S). *Journal of Personality Assessment, 91*, 166–174. https://doi.org/10.1080/00223890802634290

Duncan, T. G., & McKeachie, W. J. (2005). The making of the motivated strategies for learning questionnaire. *Educational Psychologist, 40*(2), 117–128. https://doi.org/10.1207/s15326985ep4002_6

Dupeyrat, C., & Mariné, C. (2005). Implicit theories of intelligence, goal orientation, cognitive engagement, and achievement: A test of Dweck's model with returning to school adults. *Contemporary Educational Psychology, 30*(1), 43–59. https://doi.org/10.1016/j.cedpsych.2004.01.007

Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development (1st Ed.)*. Psychology press. https://doi.org/10.4324/9781315783048

Dweck, C. (2017). *Mindset-updated edition: Changing the way you think to fulfil your potential*. Hachette UK.

Dweck, C. (2015). Carol Dweck revisits the growth mindset. *Education Week, 35*(5), 20–24.

Dweck, C. S., Chiu, C., & Hong, Y. (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological Inquiry, 6*(4), 267–285. https://doi.org/10.1207/s15327965pli0604_1

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256–273. https://doi.org/10.1037/0033-295x.95.2.256

Dweck, C. S., & Yeager, D. S. (2019). Mindsets: A view from two eras. *Perspectives on Psychological Science, 14*(3), 481–496. https://doi.org/10.1177/1745691618804166

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist, 46*(1), 6–25. https://doi.org/10.1080/00461520.2011.538645

Elliot, A. J., & Murayama, K. (2008). On the measurement of achievement goals: Critique, illustration, and application. *Journal of Educational Psychology, 100*(3), 613–628. https://doi.org/10.1037/0022-0663.100.3.613

Greenglass, E. R. (2002). Proactive coping and quality of life management. *In Beyond coping: Meeting goals, visions,and challenges* (pp. 37–62). Oxford University Press. https://doi.org/10.1093/med:psych/9780198508144.003.0003

Harackiewicz, J. M., Durik, A. M., Barron, K. E., Linnenbrink-Garcia, L., & Tauer, J. M. (2008). The role of achievement goals in the development of interest: Reciprocal relations between achievement goals, interest, and performance. *Journal of Educational Psychology, 100*(1), 105–122. https://doi.org/10.1037/0022-0663.100.1.105

Haimovitz, K., & Dweck, C. S. (2017). The origins of children's growth and fixed mindsets: New research and a new proposal. *Child Development, 88*(6), 1849–1859. https://doi.org/10.1111/cdev.12955

Hecht, C. A., Dweck, C. S., Murphy, M. C., Kroeper, K. M., & Yeager, D. S. (2023). Efficiently exploring the causal role of contextual moderators in behavioral science. *Proceedings of the National Academy of Sciences, 120*(1), e2216315120. https://doi.org/10.1073/pnas.2216315120

Hong, Y.-Y., Chiu, C.-Y., Dweck, C. S., Lin, D. M. S., & Wan, W. (1999). Implicit theories, attributions, and coping: A meaning system approach. *Journal of Personality and Social Psychology, 77*, 588–599. https://doi.org/10.1037/0022-3514.77.3.588

Hu, J., & Zhang, Y. (2024). Growth mindset mediates perceptions of teachers' and parents' process feedback in digital reading performance: Evidence from 32 OECD countries. *Learning and Instruction, 90*, 101874. https://doi.org/10.1016/j.learninstruc.2024.101874

Karlen, Y., Hirt, C. N., Liska, A., & Stebner, F. (2021). Mindsets and self-concepts about self-regulated learning: Their relationships with emotions, strategy knowledge, and academic achievement [Original research]. *Frontiers in Psychology, 12*, 661142. https://doi.org/10.3389/fpsyg.2021.661142

Kim, Y.-e., Yu, S. L., Wolters, C. A., & Anderman, E. M. (2023). Self-regulatory processes within and between diverse goals: The multiple goals regulation framework. *Educational Psychologist*, 1–22. https://doi.org/10.1080/00461520.2022.2158828

King, R. B. (2019). Mindsets are contagious: The social contagion of implicit theories of intelligence among classmates. *British Journal of Educational Psychology*. https://doi.org/10.1111/bjep.12285

Kroeper, K. M., Fried, A. C., & Murphy, M. C. (2022a). Towards fostering growth mindset classrooms: Identifying teaching behaviors that signal instructors' fixed and growth mindsets beliefs to students. *Social Psychology of Education, 25*(2), 371–398. https://doi.org/10.1007/s11218-022-09689-4

Kroeper, K. M., Muenks, K., Canning, E. A., & Murphy, M. C. (2022b). An exploratory study of the behaviors that communicate perceived instructor mindset beliefs in college STEM classrooms. *Teaching and Teacher Education, 114*, 103717. https://doi.org/10.1016/j.tate.2022.103717

Laine, S., & Tirri, K. (2023). Literature review on teachers' mindsets, growth-oriented practices and why they matter [Review]. *Frontiers in Education*. https://doi.org/10.3389/feduc.2023.1275126

Lam, K. K. L., & Zhou, M. (2020). A serial mediation model testing growth mindset, life satisfaction, and perceived distress as predictors of perseverance of effort. *Personality and Individual Differences, 167*, 110262. https://doi.org/10.1016/j.paid.2020.110262

Lee, H. J., Lee, J., Song, J., Kim, S., & Bong, M. (2022). Promoting children's math motivation by changing parents' gender stereotypes and expectations for math. *Journal of Educational Psychology, 114*, 1567–1588. https://doi.org/10.1037/edu0000743

Li, Y., & Bates, T. C. (2020). Testing the association of growth mindset and grades across a challenging transition: Is growth mindset associated with grades? *Intelligence, 81*, 101471. https://doi.org/10.1016/j.intell.2020.101471

Linacre, J. (2006). *A users guide to WINSTEPS Ministep: Rasch-model computer programs*. Winsteps. https://www.winsteps.com/winman/copyright.htm

Lou, N. M., & Noels, K. A. (2016). Changing language mindsets: Implications for goal orientations and responses to failure in and outside the second language classroom. *Contemporary Educational Psychology, 46*, 22–33. https://doi.org/10.1016/j.cedpsych.2016.03.004

Lou, N. M., Chaffee, K. E., & Noels, K. A. (2022). Growth, fixed, and mixed mindsets: Mindset system profiles in foreign language learners and their role in engagement and achievement. *Studies in Second Language Acquisition, 44*(3), 607–632. https://doi.org/10.1017/S0272263121000401

Lou, N. M., & Li, L. M. W. (2023). The mindsets × societal norm effect across 78 cultures: Growth mindsets are linked to performance weakly and well-being negatively in societies with fixed-mindset norms. *British Journal of Educational Psychology, 93*(1), 134–152. https://doi.org/10.1111/bjep.12544

Lou, N. M., & Noels, K. A. (2019). Promoting growth in foreign and second language education: A research agenda for mindsets in language learning and teaching. *System, 86*, 102126. https://doi.org/10.1016/j.system.2019.102126

Mackinnon, S., Curtis, R., & O'Connor, R. (2022). A tutorial in longitudinal measurement invariance and cross-lagged panel models using lavaan. *Meta-Psychology*, *6*.

Macnamara, B. N., & Burgoyne, A. P. (2022). Do growth mindset interventions impact students' academic achievement? A systematic review and meta-analysis with recommendations for best practices. *Psychological Bulletin*, No Pagination Specified-No Pagination Specified. https://doi.org/10.1037/bul0000352

Macnamara, B. N., & Burgoyne, A. P. (2023). A spotlight on bias in the growth mindset intervention literature: A reply to commentaries that contextualize the discussion (Oyserman, 2023; Yan & Schuetze, 2023) and illustrate the conclusion (Tipton et al., 2023). *Psychological Bulletin*, *149*(3–4), 242–258. https://doi.org/10.1037/bul0000394

Marsh, H. W., Hau, K.-T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural Equation Modeling: A Multidisciplinary Journal, 11*(3), 320–341. https://doi.org/10.1207/s15328007sem1103_2

Meade, A. W., Johnson, E. C., & Braddy, P. W. (2008). Power and sensitivity of alternative fit indices in tests of measurement invariance. *Journal of Applied Psychology, 93*(3), 568–592. https://doi.org/10.1037/0021-9010.93.3.568

Muenks, K., Canning, E. A., LaCosse, J., Green, D. J., Zirkel, S., Garcia, J. A., & Murphy, M. C. (2020). Does my professor think my ability can change? Students' perceptions of their STEM professors' mindset beliefs predict their psychological vulnerability, engagement, and performance in class. *Journal of Experimental Psychology: General, 149*, 2119–2144. https://doi.org/10.1037/xge0000763

Muenks, K., Kroeper, K. M., Canning, E. A., & Murphy, M. C. (2024). Instructor mindset beliefs and behaviors: How do students and instructors perceive them? *Social Psychology of Education*. https://doi.org/10.1007/s11218-024-09948-6

Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education, 31*(2), 199–218. https://doi.org/10.1080/03075070600572090

OECD. (2019). *PISA 2018 Insights and Interpretations*. Author. https://www.oecd.org/pisa/PISA%202018%20Insights%20and%20Interpretations%20FINAL%20PDF.pdf

Patall, E. A., Zambrano, J., Kennedy, A. A. U., Yates, N., & Vallín, J. A. (2022). Promoting an agentic orientation: An intervention in university psychology and physical science courses. *Journal of Educational Psychology, 114*, 368–392. https://doi.org/10.1037/edu0000614

Parada, S., & Verlhiac, J.-F. (2022). Growth mindset intervention among French university students, and its articulation with proactive coping strategies. *Educational Psychology, 42*(3), 354–374. https://doi.org/10.1080/01443410.2021.1917519

Patrick, S. K., & Joshi, E. (2019). Set in Stone" or "Willing to Grow"? Teacher sensemaking during a growth mindset initiative. *Teaching and Teacher Education, 83*(1), 156–167. https://doi.org/10.1016/j.tate.2019.04.009

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (eds.), Handbook of self-regulation (pp. 451-502). Academic Press.

Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology, 95*(4), 667–686. https://doi.org/10.1037/0022-0663.95.4.667

Pintrich, P. R., Smith, D. A. F., Garcia, T., & Mckeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (Mslq). *Educational and Psychological Measurement, 53*(3), 801–813. https://doi.org/10.1177/0013164493053003024

Qin, X., Wormington, S., Guzman-Alvarez, A., & Wang, M.-T. (2021). Why does a growth mindset intervention impact achievement differently across secondary schools? Unpacking the causal mediation mechanism from a national multisite randomized experiment. *Journal of Research on Educational Effectiveness, 14*(3), 617–644. https://doi.org/10.1080/19345747.2021.1894520

R Core Team. (2016). *R: A Language and Environment for Statistical Computing [computer software]*. In Authors. https://www.R-project.org/

Rege, M., Hanselman, P., Solli, I. F., Dweck, C. S., Ludvigsen, S., Bettinger, E., Crosnoe, R., Muller, C., Walton, G., Duckworth, A., & Yeager, D. S. (2021). How can we inspire nations of learners? An investigation of growth mindset and challenge-seeking in two countries. *American Psychologist, 76*(5), 755–767. https://doi.org/10.1037/amp0000647

Schöber, C., Schütte, K., Köller, O., McElvany, N., & Gebauer, M.M. (2018). Reciprocal effects between self-efficacy and achievement in mathematics and reading. *Learning and Individual Differences, 63*, 1–11. https://doi.org/10.1016/j.lindif.2018.01.008

Schunk, D. H., & Greene, J. A. (Eds.). (2017). *Handbook of self-regulation of learning and performance* (2nd ed.). Routledge. https://doi.org/10.4324/9781315697048

Sisk, V. F., Burgoyne, A. P., Sun, J., Butler, J. L., & Macnamara, B. N. (2018). To what extent and under which circumstances are growth mind-sets important to academic achievement? Two Meta-Analyses. *Psychological Science, 29*(4), 549–571. https://doi.org/10.1177/0956797617739704

Skinner, E. A., Rickert, N. P., Vollet, J. W., & Kindermann, T. A. (2022). The complex social ecology of academic development: A bioecological framework and illustration examining the collective effects of parents, teachers, and peers on student engagement. *Educational Psychologist, 57*(2), 87–113. https://doi.org/10.1080/00461520.2022.2038603

Sun, X., Nancekivell, S., Gelman, S. A., & Shah, P. (2021). Growth mindset and academic outcomes: A comparison of US and Chinese students. *NPJ Science of Learning, 6*(1), 21. https://doi.org/10.1038/s41539-021-00100-z

Tempelaar, D. T., Rienties, B., Giesbers, B., & Gijselaers, W. H. (2015). The pivotal role of effort beliefs in mediating implicit theories of intelligence and achievement goals and academic motivations. *Social Psychology of Education, 18*(1), 101–120. https://doi.org/10.1007/s11218-014-9281-7

Testa, I., Capasso, G., Colantonio, A., Galano, S., Marzoli, I., Scotti di Uccio, U., Trani, F., & Zappia, A. (2019). Development and validation of a university students' progression in learning quantum mechanics through exploratory factor analysis and Rasch analysis. *International Journal of Science Education, 41*(3), 388–417. https://doi.org/10.1080/09500693.2018.1556414

Veenman, M. V. J., Van Hout-Wolters, B. H. A. M., & Afflerbach, P. (2006). Metacognition and learning: Conceptual and methodological considerations. *Metacognition and Learning, 1*(1), 3–14. https://doi.org/10.1007/s11409-006-6893-0

Vu, T., Magis-Weinberg, L., Jansen, B. R. J., van Atteveldt, N., Janssen, T. W. P., Lee, N. C., van der Maas, H. L. J., Raijmakers, M. E. J., Sachisthal, M. S. M., & Meeter, M. (2022). Motivation-Achievement Cycles in Learning: A Literature Review and Research Agenda. *Educational Psychology Review, 34*(1), 39–71. https://doi.org/10.1007/s10648-021-09616-7

Willis, G. B., Miller, K., Willis, G. B., & Miller, K. (2011). Cross-cultural cognitive interviewing: Seeking comparability and enhancing understanding. *Field Methods, 23*(4), 331–341. https://doi.org/10.1177/1525822x11416092

Wilson, M. (2005). *Constructing measures: An item response modeling approach*. Lawrence Erlbaum Associates Publishers.

Wu, M. L., Adams, R. J., Wilson, M. R., & Haldane, S. A. (2007). *ACER ConQuest, Version 2.0: Generalized Item Response Modelling Software [computer software]*. In ACER Press.

Yan, Z., & Brown, G. T. L. (2017). A cyclical self-assessment process: Towards a model of how students engage in selfassessment. *Assessment & Evaluation in Higher Education, 42*(8), 1247–1262. https://doi.org/10.1080/02602938.2016.1260091

Yan, V. X., & Schuetze, B. A. (2023). What is meant by "growth mindset"? Current theory, measurement practices, and empirical results leave much open to interpretation: Commentary on Macnamara and Burgoyne (2023) and Burnette et al. (2023). *Psychological Bulletin*, *149*(3–4), 206–219. https://doi.org/10.1037/bul0000370

Yan, V. X., Thai, K. P., & Bjork, R. A. (2014). Habits and beliefs that guide self-regulated learning: Do they vary with mindset? *Journal of Applied Research in Memory and Cognition, 3*(3), 140–152. https://doi.org/10.1016/j.jarmac.2014.04.003

Yan, Z. (2020). Developing a short form of the self-assessment practices scale: Psychometric evidence. *Frontiers in Education, 4*, 153. https://doi.org/10.3389/feduc.2019.00153

Yan, Z., King, R. B., & Haw, J. Y. (2021). Formative assessment, growth mindset, and achievement: Examining their relations in the East and the West. *Assessment in Education: Principles, Policy & Practice, 28*(5–6), 676–702. https://doi.org/10.1080/0969594X.2021.1988510

Yeager, D. S., Carroll, J. M., Buontempo, J., Cimpian, A., Woody, S., Crosnoe, R., Muller, C., Murray, J., Mhatre, P., Kersting, N., Hulleman, C., Kudym, M., Murphy, M., Duckworth, A. L., Walton, G. M., & Dweck, C. S. (2022). Teacher mindsets help explain where a growth-mindset intervention does and doesn't work. *Psychological Science, 33*(1), 18–32. https://doi.org/10.1177/09567976211028984

Yeager, D. S., & Dweck, C. S. (2012). Mindsets that promote resilience: When students believe that personal characteristics can be developed. *Educational Psychologist, 47*(4), 302–314. https://doi.org/10.1080/00461520.2012.722805

Yeager, D. S., & Dweck, C. S. (2020). What can be learned from growth mindset controversies? *American Psychologist, 75*, 1269–1284. https://doi.org/10.1037/amp0000794

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., & Paunesku, D. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature, 573*(7774), 364–369. https://doi.org/10.1038/s41586-019-1466-y

Yeager, D. S., Walton, G. M., Brady, S. T., Akcinar, E. N., Paunesku, D., Keane, L., Kamentz, D., Ritter, G., Duckworth, A. L., Urstein, R., Gomez, E. M., Markus, H. R., Cohen, G. L., & Dweck, C. S. (2016). Teaching a lay theory before college narrows achievement gaps at scale. *Proceedings of the National Academy of Sciences, 113*(24), E3341–E3348. https://doi.org/10.1073/pnas.1524360113

Zeng, G., Hou, H., & Peng, K. (1873). Effect of growth mindset on school engagement and psychological well-being of Chinese primary and middle school students: The mediating role of resilience. *Frontiers in Psychology, 2016*, 7.

Zimmerman, B.J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

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