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REVIEW ARTICLE

Motivation-Achievement Cycles in Learning: a Literature Review and Research Agenda

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Abstract
The question of how learners' motivation influences their academic achievement and vice versa has been the subject of intensive research due to its theoretical relevance and important implications for the field of education. Here, we present our understanding of how influential theories of academic motivation have conceptualized reciprocal interactions between motivation and achievement and the kinds of evidence that support this reciprocity. While the reciprocal nature of the relationship between motivation and academic achievement has been established in the literature, further insights into several features of this relationship are still lacking. We therefore present a research agenda where we identify theoretical and methodological challenges that could inspire further understanding of the reciprocal relationship between motivation and achievement as well as inform future interventions. Specifically, the research agenda includes the recommendation that future research considers (1) multiple motivation constructs, (2) behavioral mediators, (3) a network approach, (4) alignment of intervals of measurement and the short vs. long time scales of motivation constructs, (5) designs that meet the criteria for making causal, reciprocal inferences, (6) appropriate statistical models, (7) alternatives to self-reports, (8) different ways of measuring achievement, and (9) generalizability of the reciprocal relations to various developmental, ethnic, and sociocultural groups.

Keywords Learning · Motivation · Academic achievement · Reciprocal · Review

Introduction

In most countries, motivation for school clearly declines throughout school time (Martin, 2009; OECD, 2016; Scherrer & Preckel, 2019) with individual heterogeneity in changes depending on specific motivation constructs across academic domains (Gaspard et al., 2020;

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Scherrer & Preckel, 2019). Given this undesirable decline and the fact that motivation can be targeted by interventions, motivation has long been a central focus of educational psychology. The influence of motivation on achievement is well-documented (Burnette et al., 2013; Gottfried et al., 2013; Greene & Azevedo, 2007; Valentine et al., 2004). Yet the reverse relation is also often found, as achievement can affect motivation through experiences of success or failure (Garon-Carrier et al., 2016; Guay et al., 2003; Jansen et al., 2013). A common view is that both the "motivation → achievement" and "achievement → motivation" links exist and that motivation and achievement influence each other in a reciprocal manner over time (Huang, 2011; Marsh & Craven, 2006; Marsh & Martin, 2011; Möller et al., 2009).

Researchers have been studying this reciprocal relationship between motivation and achievement for at least 20 years (Marsh et al., 1999). However, further insights into the nature of the relationship are currently lacking; features such as the direction of causality, behavioral mediating pathways, possible effect of the time scale, and generalizations to different motivation constructs and population groups are currently not well understood. These issues are important not just from a scientific viewpoint, but also from a practical viewpoint. To be able to design the most effective interventions aimed at improving achievement and motivation, we need to improve our understanding of the reciprocity to identify the best timing, duration, content, and appropriate target variables of such interventions, as well as other contextual factors contributing to their success.

Our objective is to summarize the current understanding of motivation-achievement interactions (drawing mainly from the academic motivation literature) and to identify the theoretical and methodological challenges that could inspire further advances to understand such specific features of this reciprocal relationship. While an exhaustive review of the literature is beyond the scope of the current paper (see the Special Issue on Prominent Motivation Theories: The Past, Present, and Future on Contemporary Educational Psychology, edited by Wigfield and Koenka, 2020), we start with a summary of how influential theories of academic motivation have conceptualized reciprocity between motivation and achievement, and the types of empirical evidence that have been found in support of the reciprocal relationships. In our current understanding, we have found areas of consensus, but have also identified sizable gaps. This leads to a recommended research agenda for future empirical studies on the reciprocal relations between motivation and academic achievement and suggestions on how these insights could inform future interventions.

Reciprocal Relations in Theories of Academic Motivation

Commonalities Between Theories

Individual differences in academic achievement are partly the result of differences in motivation for learning (Arens et al., 2017; Burnette et al., 2013; Eccles & Wigfield, 2002; Guay et al., 2003; Huang, 2011; Marsh & Craven, 2006; Marsh & Martin, 2011; Robbins et al., 2004; Seaton et al., 2014). This robust finding has spawned a wealth of theories on academic motivation and how to stimulate it. These theories differ in both substance and focus, but also have many common elements. Figure 1 represents an attempt to synthesize, for the purposes of this paper, some of the commonalities of well-established theories that have had an impact in the field of academic motivation (leaning strongly on the seminal review of Eccles & Wigfield, 2002 and adding theories that have gained traction since). Our goal is not to

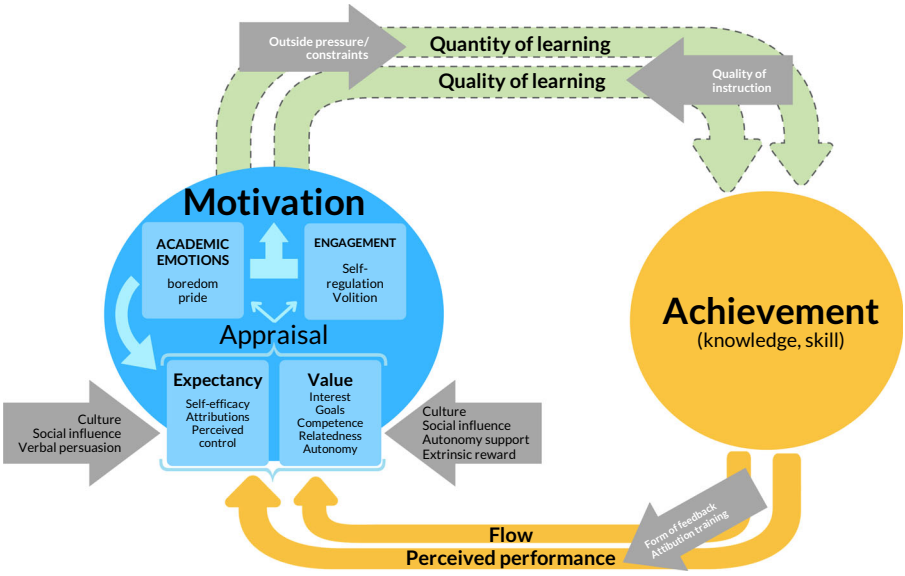

Fig. 1 The motivation-achievement cycle, a summary model of motivation-achievement interactions, capturing some of the commonalities within prominent theories of academic motivation. Blue boxes denote motivation constructs, green (dotted) arrows behavioral intermediaries (quality of learning and quantity of learning), and yellow boxes and arrows denote achievement-related constructs (flow and perceived performance). Gray arrows denote outside influences that are themselves not part of motivation-achievement interactions (e.g., cultural and social influences that affect both expectancies and values)

comprehensively review and synthesize the existing theories (although this is an urgent task, Koenka, 2020), but rather to illustrate how the commonalities between the theories suggest a framework in which the reciprocal relationships between motivation and achievement can be studied and understood.

Motivation has up to 102 definitions (Kleinginna & Kleinginna, 1981), but is often seen as a condition that energizes (or de-energizes) behaviors. In many theories, motivation results from what can be called an appraisal of the behavior that one is motivated to perform (the word appraisal is rarely used with regard to motivation, but the processes described are akin to those captured in the emotion literature). In that appraisal, two elements are combined (Eccles & Wigfield, 2002): the value attached to the behavior and its outcomes, and the expectancy of the likelihood of certain outcomes of the behavior. These two sides, expectancy and value, are explicit in expectancy-value theory (Eccles & Wigfield, 2002, 2020), attribution theory (Graham, 2020; Weiner, 2010), control-value theory (Pekrun, 2006; Pekrun et al., 2017), and Dweck's integrative theory (Dweck, 2017).

Many other theories focus either on the value attached to behavior or on expectancies. Theories on the values side of the ledger (goal theories, flow theory, self-determination theory, individual differences theories, and interest theories) focus on interest, goals, needs for relatedness, competence, and autonomy. Theories on the expectancy side, notably self-efficacy theory, control theories, social-cognitive self-regulation theories, and the process-oriented metacognitive model, focus on how students' beliefs (or perception) about their competence and efficacy (i.e., academic self-concept, see below), expectancies for success or failure, and sense of control over achievement affect motivation. Different constructs have been studied that tap into these beliefs underlying one's expectancies, such as academic self-concept, self-efficacy, locus of control, and perceived control.

A motivation construct frequently used to study the reciprocal motivation-achievement relationship is *academic self-concept* (hitherto, ASC, discussed in further details in section "Different motivation constructs" below) which is how individuals evaluate their ability specifically in an academic domain (Marsh & Craven, 2006; Marsh & Martin, 2011; Shavelson et al., 1976). ASC is a component distinct from physical, social, and emotional self-concepts within the multidimensional, hierarchical model of self-concept (Marsh & Craven, 2006; Marsh & Martin, 2011). ASC is itself also multidimensional and usually measured by the Self Description Questionnaire (Marsh et al., 1999; Marsh & O'Neill, 1984); its academic subscales tap into general academic self-concept, math self-concept, and verbal self-concept. Much empirical research on motivation-achievement interactions operationalizes motivation as ASC in a certain academic domain, most often in mathematics and verbal subjects such as language and reading (Guay et al., 2003; Seaton et al., 2014); for meta-analyses and reviews, see Burnette et al. (2013), Eccles and Wigfield (2002), Marsh and Craven (2006), Marsh and Martin (2011), and Robbins et al. (2004).

It is worth noting that many theories posit that beliefs about the self (including self-concept and self-esteem and mindset/implicit theory of self attributes) are important *causes* of human behavior and learning (Bandura, 1997; Carver & White, 1994; Deci & Ryan, 2000; Molden & Dweck, 2006). Although the idea that ASC or other beliefs about the self affect achievement has been challenged (see the discussion in Marsh & Craven, 2006), there has also been much empirical research in support of it (Burnette et al., 2013; Gottfried et al., 2013; Greene & Azevedo, 2007; and the meta-analyses of Huang, 2011; Valentine et al., 2004). One suggested pathway is that positive self-beliefs can lead to self-affirmative, self-regulatory, academic behaviors (or *achievement behaviors*, see below) such as exerting effort, demonstrating persistence, and selecting goals that are conducive to the achievement of academic goals.

Another pathway for beliefs about the self to act as a causal agent on academic achievement, according to self-worth theory (Covington, 2000), is that students with positive beliefs about themselves assign high and positive values to academic activities. Academic activities are then viewed as important, intrinsically interesting, of high expected utility and of low cost, which leads to high achievement (Valentine et al., 2004). Also, in self-determination theory, feelings of competence are a precursor of intrinsic motivation, again leading to a higher value being assigned to academic activities if one feels competent. This would then lead to behaviors that support later achievement. A recent study of more than 30,000 college students found that need for competence (relative to need for autonomy and relatedness) is the strongest predictor of perceived learning gains (Yu & Levesque-Bristol, 2020).

An appraisal of values and expectancies leads to the decision to engage (Cleary & Zimmerman, 2012; Kuhl, 1984; Schunk & DiBenedetto, 2020). According to the self-regulatory account of motivation (Cleary & Zimmerman, 2012; Schunk & DiBenedetto, 2020), students first identify values and expectancy of learning activities, then engage in self-regulatory processes (self-instruction, attention focusing, task strategies, etc.). Following their performance, students conduct self-evaluations, infer causal attributions, and make adaptive or maladaptive attributions of their successes and failures. This account stresses the importance of metacognition, where students who can monitor their learning processes can then maintain their engagement in the learning cycle.

The appraisal of values and expectancies can also trigger academic emotions, such as pride in achievement, hope, boredom, and enjoyment. Control-value theory (Pekrun, 2006; Pekrun et al., 2017) describes how such emotions codetermine what are termed *achievement behaviors*—behaviors that are conducive to the achievement of academic goals. In line with

dominant theories of emotion (e.g. Frijda, 1988; Lazarus, 1999), Pekrun (2006) assumed that an appraisal of control of the learner and the value of learning activities lie at the basis of academic emotions. For example, if a learner values an academic outcome and believes it is somewhat under his or her control, he or she may feel the emotion of hope. While it is not certain that the same kinds of appraisal lie at the basis of both motivation and academic emotions, it would seem plausible and parsimonious. Indeed, Pekrun (2006) suggested that this is the case, though he cautioned that more research is needed.

Figure 1 may raise the question of what actually distinguishes motivation from emotions, since both seem to result from an appraisal of the situation, and both energize or de-energize certain behaviors. This is a valid question, and Kleinginna and Kleinginna (1981) already noted that a sharp line between motivation and emotion is difficult to draw (also see Berridge, 2018). Emotions will typically be more temporary than motivation, but this is a fuzzy distinction. Emotions and motivation may also interact. Emotions may for example make a learner assign more or less value to academic activities, or may change the learner's expectations around their chances of success or failure, which then changes the appraisal that underlies motivation. Literature showing that emotions and academic achievement also form reciprocal relationships over time has recently emerged (Putwain et al., 2018).

Pathways from Motivation to Achievement and Vice Versa

While it is generally accepted that motivation affects achievement, it is not completely clear *how*. Theoretically, two routes can be discerned (see Fig. 1). The *first* is the quantity (frequency and intensity) of academic behaviors aimed at achievement (such as effort, persistence, etc.) (Cury et al., 2008; Dettmers et al., 2009; Doumen et al., 2014; Marsh et al., 2016; Pinxten et al., 2014; Plant et al., 2005; Trautwein et al., 2009). As a *second* route, higher levels of motivation could also be associated with higher quality of academic behaviors; for example, by adopting effective learning strategies, adaptive meta-cognitive strategies, spaced practice, elaboration, retrieval practice, interleaving, dual coding, and so on. Several theories of academic motivation support the idea that higher motivation leads to higher quality behaviors. Both intrinsic motivation (self-determination theory, Deci & Ryan, 2000) and interest (interest theories, Alexander et al., 1994) have been linked to deeper learning (Alexander et al., 1994; Schiefele, 1999; Scott Rigby et al., 1992). Positive academic motivations have also been suggested to facilitate creative learning strategies (control-value theory, Pekrun, 2006), and incremental implicit beliefs (growth mindset) to facilitate mastery-oriented strategies (Burnette et al., 2013).

Effects of achievement on motivation may also take two routes. The *first* is through perceived achievement. Many theories, such as self-efficacy theory (Bandura, 1997), expectancy-value theory (Eccles & Wigfield, 2002), control theories (Skinner, 1995), and attribution theory (Weiner, 2010) explicitly suggest that past achievement leads a learner to experience feelings of self-efficacy and perception of control. What matters most in this regard is the learner's own evaluation of this outcome, for which we use the term perceived performance in Fig. 1. High perceived performance will thus change the expectancies of learners (i.e., make them trust that good outcomes are attainable), but it may also alter the value attached to learning activities. For example, in self-determination theory, the feeling of competence (strengthened by positive perceived achievement) is a basic need that increases the intrinsic value of learning.

The *second* route from achievement to motivation is central to flow theory (Csikzentmihalyi, 1990). An activity in which the learner is holistically immersed can generate a feeling of flow, which is rewarding in its own right and alters the value attached to the academic behaviors.

External Factors Affecting Motivation, Effort, and Achievement

Figure 1 suggests a positive feedback loop, with motivation feeding achievement, and achievement feeding motivation—an idea that is alluded to in some theories (Cleary & Zimmerman, 2012; Eccles & Wigfield, 2002; Schunk & DiBenedetto, 2020). Most explicit in this regard is the self-regulatory account of motivation (Cleary & Zimmerman, 2012) where the pathway between self-regulation and achievement is a cyclical feedback loop. Schunk and DiBenedetto (2020) suggest an iterative process between perceived progress, self-efficacy, and goal pursuit. Bandura's social cognitive theory also stresses the reciprocity of the interactions between behavioral, environmental, and personal factors (Bandura, 1997). Crucially, this raises the question of how such a positive feedback loop could get started, and how, once started, it could lead to any other outcome than either perfect motivation and achievement, or negative motivation and failure. The answer to those questions may rest in the *external influences* on motivation and achievement. These are indicated in Fig. 1 by the gray arrows:

- Extrinsic rewards and requirements tied to achievement, e.g., schools or parents, may change the value attributed to academic behavior, and so change motivation. Although this has been described in self-determination theory as potentially detracting from intrinsic motivation (Deci & Ryan, 2000), it may also jolt a motivation-achievement cycle that would otherwise not start (Hidi & Harackiewicz, 2001). Supporting autonomy and creating relatedness are other ways in which external actors can increase the value attached to learning, increasing motivation and achievement (Deci & Ryan, 2000).
- Cultural norms (described in control theories and control-value theory, Pekrun, 2006; Skinner, 1995), social learning, and verbal persuasion by others (social cognitive theory, Bandura, 1997) can alter the expectations, values, and attributional processes of learners (expectancy-value theory, attribution theories, Eccles & Wigfield, 2020; Graham, 2020), and therefore keep a motivation-achievement cycle going that would otherwise falter or not start up.
- Effort is not only a result of the learner's motivation but also of outside requirements (e.g., deadlines and exams set by the educational institution, Kerdijk et al., 2015). Such outside requirements can lead to achievement in the absence of strong motivation.
- Quality of learning is not only affected by motivation but also by the abilities of the learner and the quality of teaching, instructions, and study materials. Thus, achievement can increase in the absence of stronger motivation, because of better support for learning.
- Perceived achievement is not only determined by true achievement but also by elements of educational design, such as the form in which feedback is given (e.g., a grade that either accentuates the ranking of the student or the degree to which the study material was mastered, or feedback on effort instead of performance, De Kraker-Pauw et al., 2017). Perceived achievement is also subject to interpretative, comparison, and attributional processes (described in attribution theories, Graham, 2020; Weiner, 2010). This means that true high achievement can still fail to support motivation (e.g., when a sibling performs

even better), or low achievement can be viewed in such a way so as to not be detrimental for motivation.

Such external factors are not only important for a complete causal understanding of motivation-achievement interactions (i.e., highly relevant for educational researchers) but also because they offer entry points for interventions that enhance motivation, achievement, or both (i.e., highly relevant for educators).

What Avenues for Empirical Research Have Been Explored?

Figure 1 shows that theories of academic achievement imply a reciprocal relationship between motivation and achievement. A comprehensive review of studies is beyond the scope of this manuscript (see narrative reviews and meta-analyses) (Huang, 2011; Marsh & Craven, 2006; Scharmer, 2020; Valentine et al., 2004; Valentine & Dubois, 2005), but we will review the kinds of evidence that have been brought to bear in support of such reciprocal relationships. Analyzing this evidence allows future directions on the field to be charted.

The earliest support for the relationship between motivation (focusing specifically on self-concepts and other self beliefs) and academic achievement comes from cross-sectional and correlational studies, reviewed by Hansford and Hattie (1982). These studies established a relationship between self-concepts and academic achievement, but no causal paths. Subsequent work set out to investigate the causal and temporal ordering of the effects using structural equation models (SEMs) and longitudinal data (e.g., Marsh et al., 1999). To date, the majority of evidence for the reciprocal relationship between self-concept and achievement has come from such time-series or cross-sectional data collected at schools, to which various SEMs have been fitted (see Marsh & Craven, 2006 for a narrative review and Huang, 2011 for a meta-analysis of such studies).

More recent studies showcase impressive efforts of researchers to use large sample sizes and longitudinal data of up to six waves, allowing changes in motivation and achievement of students to be tracked across their school career (e.g., Marsh et al., 2018; Murayama et al., 2013). A recent meta-analysis (Scharmer, 2020), which includes such studies that were published between 2011 and August 2020, showed that overall, the pooled effect of achievement on motivation was twice ($\beta = .12$) the pooled effect of motivation on achievement ($\beta = .06$), though both are what is conventionally considered a small effect. These findings are in line with Valentine and DuBois (2005) who found that academic achievement had a stronger effect on self-belief than vice versa. In contrast, Huang (2011)'s meta-analysis found a slightly larger effect of self-concept on achievement than the other way around. Valentine and DuBois (2005)'s findings were also more similar to Scharmer's (2020) in terms of the size of the effects (achievement on self-belief: $\beta = 0.08$; self-belief on achievement: $\beta = 0.15$). Huang (2011), however, found considerably larger ranges of effects overall (achievement on self-concept: $\beta = 0.19–0.25$; self-concept on achievement: $\beta = 0.20–0.27$).

There have also been interventions and randomized controlled field studies in which either self-concept or other motivation constructs were manipulated (e.g., Savi et al., 2018; Vansteenkiste et al., 2004), thereby allowing for causal inferences. The meta-analysis of these studies by Lazowski and Hulleman (2016) showed that, while interventions targeting motivation usually led to positive outcomes on achievement (medium effect size; average Cohen's *d* of 0.49), it did not matter which theory was at the basis of the intervention— all theories of motivation performed about equally well. However, experimental studies that look at the

reverse causal path, manipulating achievement (or the perception of achievement) to affect motivation, are scarce. One example is an intervention study by Betz and Schifano (2000) where students were ensured of successful completion of a task followed by affirmation of their accomplishments with applause and verbal praise. This resulted in an increase in self-efficacy (a motivation construct highly related to ASC, Bong & Skaalvik, 2003). Nevertheless, to the best of our knowledge, few studies have done both: combining experimental manipulation *and* longitudinal design to investigate reciprocal motivation-achievement relations (an exception that we are aware of is Bejjani et al., 2019 which will be discussed later).

Research Agenda

The overview given above suggests that empirical evidence for reciprocal relations between motivation and achievement exists. However, several features of such relationships are still poorly understood. Also, some doubts about the robustness of the effects have recently surfaced (which we discuss in detail in section "Choice of appropriate statistical models" below). In other words, there are still unanswered theoretical and empirical questions about the reciprocal relationship between motivation and academic achievement. Below, we outline these issues and a *research agenda* for future research that can answer these remaining questions. These are organized into questions pertaining to theoretical lacunae, methodological challenges, and questions about the scope of theories and the generalizability of empirical results.

Theoretical Lacunae

Multiple Motivation Constructs

First, as we presented above, many motivation theories have implicitly or explicitly conceptualized the relationship between a plethora of motivation constructs and achievement as reciprocal. However, to date, a large amount of empirical research on reciprocal motivation-achievement interactions has mainly studied *ASC* (Arens et al., 2019; Brunner et al., 2010; Chen et al., 2013; Dicke et al., 2018; Gottfried et al., 2013; Grygiel et al., 2017; Guay et al., 2003; Guo et al., 2015; Möller et al., 2011; Niepel et al., 2014a, 2014b; Retelsdorf et al., 2014; Viljaranta et al., 2014; Walgermo et al., 2018; for meta-analyses and reviews, see Marsh & Craven, 2006; Marsh & Martin, 2011; Valentine et al., 2004; Valentine & Dubois, 2005). This raises the question of whether findings generalize to other motivation constructs that are related yet could also have a distinctive reciprocal relationship with academic achievement.

Moreover, although the studies involving ASC were groundbreaking attempts to show reciprocal relations, there are several reasons why future studies should contemplate using different motivation constructs other than ASC. First and foremost, ASC and achievement are highly intertwined, as items in ASC questionnaires usually ask students to report on their achievement (e.g., "I get good marks in most academic subjects," "I learn quickly in most academic subjects" (Marsh & O'Neill, 1984). Fulmer and Frijters (2009, p. 228) in their critique of how motivation is measured in educational psychology also made the point that "self-report measures confound the measurement of motivation with other variables, such as ability and attention."

Second, a meta-analysis investigating mean-level changes of a number of important motivation constructs concluded that the decline in motivation shows non-trivial differences across these constructs (Scherrer & Preckel, 2019). An important implication of this finding is that more attention should be paid to differentiation among multiple motivation constructs in future empirical studies.

Third, ASC might also be less malleable than other motivation constructs since general self-concept is relatively stable—especially for those at lower levels (Scherbaum et al., 2006). Research into the Big-Fish-Little-Pond phenomenon (i.e., students in high-achieving classes having lower ASC than those with comparable aptitude in regular classes) suggests that domain-specific ASC (more so than general ASC) is influenced by social comparison (Fang et al., 2018; Marsh et al., 2018). Nevertheless, it may be hard to manipulate ASC in a randomized controlled trial (although it has been indirectly done by affirming general self-esteem and personal values, Cohen et al., 2009). Other motivation constructs that can be modified through external influences (e.g., situational interest, perceived control, etc.) might yield useful guidance for designing interventions.

Furthermore, the heavy focus on ASC may reflect an emphasis on a cognitive, intrapsychological theoretical view of motivation while losing sight of social, contextual, historical, and environmental factors that arguably also play important roles (see the Special Issue on Prominent Motivation Theories: The Past, Present, and Future on Contemporary Educational Psychology, edited by Wigfield and Koenka, 2020). Last but not least, ASC is mainly self-reported and, despite the availability of well-constructed measures, it suffers from all the caveats inherent to self-report measures (see section "Alternatives to self-reports" below).

Given that there are other well-studied motivation constructs such as achievement goals, self-efficacy, interest, and intrinsic motivation (Scherrer et al., 2020; Scherrer & Preckel, 2019), further research with multiple non-ASC motivation constructs included as concomitant predictors of academic achievement is therefore much needed. In recent investigations of the reciprocal relationship between motivation and achievement, motivation constructs other than ASC have started to be included (e.g., self-efficacy in Grigg et al., 2018; Schöber et al., 2018; achievement goals in Scherrer et al., 2020; intrinsic motivation in Hebbecker et al., 2019; and interest in Höft & Bernholt, 2019). Yet, these studies are still small in number. Twenty-four out of 41 studies included in the meta-analysis of Scharmer (2020) still used ASC as the main motivation construct of interest.

Behaviors as Mediating Factors in the Motivation → Achievement Link

As mentioned above, theories of academic motivation imply several pathways through which motivation influences achievement and vice versa (see Fig. 1). For the motivation → achievement link, the rationale is that motivation leads to active and effortful commitment to learning (e.g., E. Skinner et al., 1990), implying that motivation constructs that are beliefs about competence and efficacy influence achievement by inducing self-regulatory, academic behaviors. In a similar vein, the volition theory of motivation (Eccles & Wigfield, 2002; Kuhl, 1984) posits that motivational beliefs only lead to the decision to act. Once the individual engages in action, volitional processes are required and determine whether the intention is fulfilled. Thus, self-regulatory processes theoretically mediate the link between beliefs and accomplishment of the task.

However, there is a relative paucity of empirical research and especially longitudinal studies that include measures of such regulatory processes. Usually, when studies found reciprocal relations between ASC and other motivation constructs and achievement, they left unanswered which pathways mediate the link between such beliefs and achievement (Marsh & Martin, 2011). To our knowledge, initial attempts to study mediating processes in longitudinal designs (Marsh et al., 2016; Pinxten et al., 2014; Trautwein et al., 2009) yielded mixed findings with regards to the role of effort in the relationship between ASC and academic achievement. This may be due to the fact that there are multiple operationalizations and evaluations of the construct *effort* (Massin, 2017), which may have varying relations with academic achievement. Specifically, Marsh et al. (2016) and Pinxten et al. (2014) measured *subjective* effort—i.e., students were asked to rate their own effort expenditure. Students might perceive that having to try hard (i.e., expending a great deal of effort) is indicative of a lack of academic ability (Baars et al., 2020). Subjective effort, as opposed to objective effort, might therefore have a very different relation to motivation and achievement.

In non-longitudinal studies looking at the relations between academic motivation and achievement, the evidence on behavioral mediators also shows differentiation related to how effort is measured. When effort is measured as quality of learning (e.g., selecting adaptive goals, adopting higher-quality learning strategies, etc.), there is some evidence for a positive link between academic achievement and effort (Trigwell et al., 2013). However, when effort is measured as a *quantity* of learning (such as study time, practice time, time-on-task, persistence, etc.), this relationship seems either weak or only significant after controlling for quality of learning (Cury et al., 2008; Dettmers et al., 2009; Doumen et al., 2014; Plant et al., 2005) or even negative (the labour-in-vain effect, Koriat et al., 2006; Nelson & Leonesio, 1988; Undorf & Ackerman, 2017). This provides suggestions for future attempts to parse the mediating factors in the motivation → achievement link in reciprocal relations between these two constructs. It is most fruitful to measure subjective and objective measures of quantity and quality of learning (and use triangulation of methods, as strongly suggested by Scheiter et al., 2020) and compare their effects on academic achievement.

Irrespective of what operationalization is chosen, it is important to note that it is not trivial to evaluate and conceptualize effort (see extensive discussions in Baars et al., 2020; Scheiter et al., 2020). Is effort the allocation of cognitive control, i.e., mental effort (Kool & Botvinick, 2018), or the intention to think deeply, regardless of the amount of time spent (Haynes et al., 2016), or a preference for thinking hard (Beck, 1990), a decision process rather than a capacity or resource that is physically limited (Gendolla & Richter, 2010)? Yet, only by measuring regulatory processes that mediate the motivation → achievement pathway, we can make progress in understanding the underlying mechanism of mutual influences between motivation and achievement.

Mutualistic Perspective and the Network Approach

Next, studies have typically investigated relations between one or a small number of motivation constructs (e.g., ASC and interest, Walgermo et al., 2018). The discussion above and Fig. 1 show that multiple motivation constructs are linked to academic achievement, which may also all be mutually related. Like many topics in psychology, there is a huge overlap in terms and variables in the literature on motivation and achievement; the same construct may have different names, or different constructs go under the same name (this is known as Jingle-Jangle fallacies; e.g., Marsh et al., 2003). One possible solution to the Jingle-Jangle fallacies with regard to

motivation was proposed by Marsh et al. (2003), who presented a factor model with two higher-order factors (dubbed *learning* and *performance*) that explained relations between motivation constructs. In this approach, assumptions on the number of factors and factor structure are necessary.

The network approach is different; it does not assume an a priori structure of motivation factors. Instead, it uses the (bidirectional) partial correlations between variables in empirical data and in doing so clusters of variables which can be interpreted as constructs may emerge. The idea of a network of mutual relations to model psychological constructs was introduced by van der Maas and colleagues (van der Maas et al., 2006, 2017) as an explanation for the positive correlations (the positive manifold) between intelligence sub-test scores. This led to a productive area of research with applications in many areas of psychology (Dalege et al., 2016; Robinaugh et al., 2020; Sachisthal et al., 2019, 2020; Zwicker et al., 2020). The general hypothesis in psychological network models is that correlations between observed behaviors, such as cognitive functions, psychopathological symptoms, and attitudes (or, *motivation constructs*), are not due to unobserved common causes, but to a network of interacting psychological, social, and/or biological factors. These observed behaviors are the nodes in the network and the partial correlations are the edges.

An example of how such a network approach can be applied to the area of motivation can be found in a study of interest in science (Sachisthal et al., 2019). This study included measures of students' value of science, their science engagement, and achievement. The correlations between these measures were modeled as a network, within which clusters of variables emerged. These can be seen as empirically derived constructs, replacing the at times arbitrary theoretical separation between (motivation) constructs. Given that in motivation research many constructs with considerable overlap exist (Anderman, 2020; Hattie et al., 2020), such empirically derived concepts may prove especially relevant.

Within this network, variables with the strongest direct relationships can be identified. A positive change in a central variable should lead to a positive change throughout the network and these central variables may differ between contexts. For example, enjoyment emerged as the central node in the network of Dutch students, whereas engagement behaviors emerged as central in the network of Colombian students and therefore different approaches for increasing science interest are advised for the two countries (Sachisthal et al., 2019). Central variables may be efficient intervention targets as interventions informed by network analyses have been shown to be highly effective as these central variables were later shown to be predictive of subsequent behaviors (e.g., Sachisthal et al., 2020). Moreover, further support for this assumption comes from a recent study by Zwicker et al. (2020) who identified guilt as the central node in the network of attitude and environmental behaviors. They then successfully manipulated guilt which increased willingness to engage in such behaviors.

In sum, these works exemplify how network approaches can be used (1) to model distinctive but highly related motivation and achievement constructs simultaneously and map their relations and (2) to derive hypotheses about which included constructs may be efficient targets for interventions (see Borsboom, 2017, for an overview). Moreover, the fact that network analyses found different central variables in different populations also showcases how such an approach can flexibly capture interactions between motivation factors in real life. Last but not least, at a more abstract level, a mutualistic network approach can potentially solve the question of the *mechanisms* of the impact of motivation on achievement (also raised in Hattie et al., 2020 as an important avenue for future research). Specifically, how clusters of motivation constructs, behavior, and achievement interact with one another can be modeled,

and how reciprocal relations between them arise over time. This can only be achieved when multiple motivation constructs are measured in one single study (as argued above in section "Multiple motivation constructs").

Time Scale of the Interactions (Short vs. Long Cycle)

Another gap in the literature that we identified is that much research on the reciprocity between motivation and achievement has been done with data collected at large time intervals, which reflect changes that happen over months or years (e.g., Harackiewicz et al., 2008; Marsh et al., 2005, 2016; Nuutila et al., 2018). For example, it is common for studies to include data collected per academic semester or year (e.g., Gottfried et al., 2013); sometimes, other time intervals have been used, such as weeks (e.g., Yeager et al., 2014). However, theories of motivation such as self-determination theory or expectancy-value theory are not formulated with an explicit time scale, and the interactions they describe seem framed in terms that suggest that the effects of motivation constructs happen without delays (i.e., on a time scale of seconds). Recent accounts of motivation are situated ones, which also call attention to fine-grained, moment-to-moment fluctuations that occur during learning engagement (Schunk & DiBenedetto, 2020). This raises the question how such fast dynamics can be captured if constructs are measured with large time lags in between.

It is possible that there are interactions between motivation and achievement at both short and long timescales, and that these are qualitatively different. We will refer to these hypothetical interactions at different time scales as short (or fast) and long (or slow) cycles between motivation and achievement. Some constructs may change in slower cycles (e.g., achievement goal orientation, mindset, academic self-concept) than others (e.g., autonomy, or even faster: emotions). In research focusing on interest and achievement emotions, for instance, a stable, so-called trait level (e.g., individual interest) is often distinguished from a shorter, task-dependent state level (e.g., situational interest) (see Hidi & Renninger, 2006; Renninger & Hidi, 2011 for interest; Pekrun, 2006 for achievement emotions). Nesselroade's (1991) model of within-person psychological change also distinguishes between state and trait. The former is rapid and potentially more easily reversed than the latter. Developmental processes are thought to underlie trait constructs, for instance suggesting that the repeated experience of a positive state (i.e., enjoyment) will lead to a positive trait value. While it has been suggested that reciprocal relations play a more central role on the trait level—e.g., explaining the stronger relations between emotion antecedents and emotions (Bieg et al., 2013), studies investigating reciprocal relations are still missing at a state (or task) level. Furthermore, the difference between slow and fast change is also more salient for certain constructs than for others. For example, in one rare study where the within-task changes in multiple motivation constructs was studied, researchers found that while students' self-efficacy generally grew throughout the progress of a task, interest did not (Niemivirta & Tapola, 2007). This suggests that when studies do not consider fast vs. long cycles of constructs, the effects of a faster changing variable on a slowly changing variable can be missed.

The remedy to these problems is to consider using data collected at either diverse time intervals or with theoretically informed time intervals to capture the ebbs and flows of the relations between constructs over time and their corresponding short and long cycles (Duff et al., 2015; McNeish & Hamaker, 2019). In addition, special attention should be paid to "short cycles"—especially since fast-changing constructs may be more effective targets for interventions. Intensive longitudinal designs can help uncover potential "real-time" causal variance

attributable to a construct that would be missed when it is measured at relatively lengthy intervals such as one academic semester or year (McNeish & Hamaker, 2019). This may also help when developmental trajectories are characterized by non-linear trends that cannot be captured by low-frequent measurements (McNeish & Hamaker, 2019). A deliberate choice of time intervals and the use of non-questionnaire measures will also be helpful in this respect (see section "Alternatives to self-reports" below).

A related but distinguishable issue is the stability of the reciprocal relation between motivation and achievement. Whether or not reciprocal effects of motivation and achievement are stable across school careers is a question with significant theoretical and practical consequences (Marsh et al., 2018). Two recent studies found motivation declines to be associated with particular academic stages, for example some constructs such as achievement goal orientation specifically dropped in the transition to secondary school (Scherrer et al., 2020). The Scherrer et al. (2020) data are however among the first longitudinal attempts that can reveal how such declines could potentially impact the reciprocity between motivation and achievement. Theoretically, one could assume that the impact of motivation on achievement is low early in a new environment (e.g., a school transition) where learners experience considerable uncertainty regarding their competence and academic standing (Eccles et al., 1993; Valentine et al., 2004). When the learning environment is stable, the impact of achievement on subsequent motivation might be more substantial. Some support for such a pattern is provided in Scherrer et al. (2020) who found the reciprocal effects only in later time points and not in earlier time points after transition into secondary school. However, these studies were not designed specifically to test the transition vs. non-transition contrast, prompting the need for subsequent longitudinal studies that focus on the effect of school transition (to our knowledge, Rudolph et al., 2001 is among the first but only has two waves of data).

Methodological Challenges

Causality

When extant research finds the relationships between motivation and achievement, the interpretation with regards to *causal relations* remains difficult due to the lack of experimental manipulation (Granger, 1980; Holland, 1986; Marsh et al., 2018; Mega et al., 2014). In almost every study investigating reciprocal motivation and achievement relations, the need for experimental designs in which either motivation or achievement is manipulated is raised as a suggestion for future research (Marsh et al., 2016, 2018; Mega et al., 2014; Pinxten et al., 2014). The term "effect" in many existing studies is used only in "conventional statistical sense and standard path analytic terminology, as representing a relation that is not necessarily causal" (Marsh et al., 2018, p. 268).

Research that aims to establish causality in the reciprocal relationship between motivation and achievement would need to meet three preconditions. The first precondition of causality is *order*, that is "x must precede y temporally" (Antonakis et al., 2010, p. 1087). Causality of reciprocal effects requires both orders (x precedes y, y precedes x), as well as alternations of x and y (x precedes y, which is again followed by x). The pale blue (with solid outline) squares in Fig. 2 show this alteration of measurements of motivation and achievement. The top pale blue rectangle starts with motivation, whereas the bottom starts with achievement. The second precondition is *correlation*: "x must be reliably correlated with y (beyond chance)" (Antonakis et al., 2010, p. 1087).

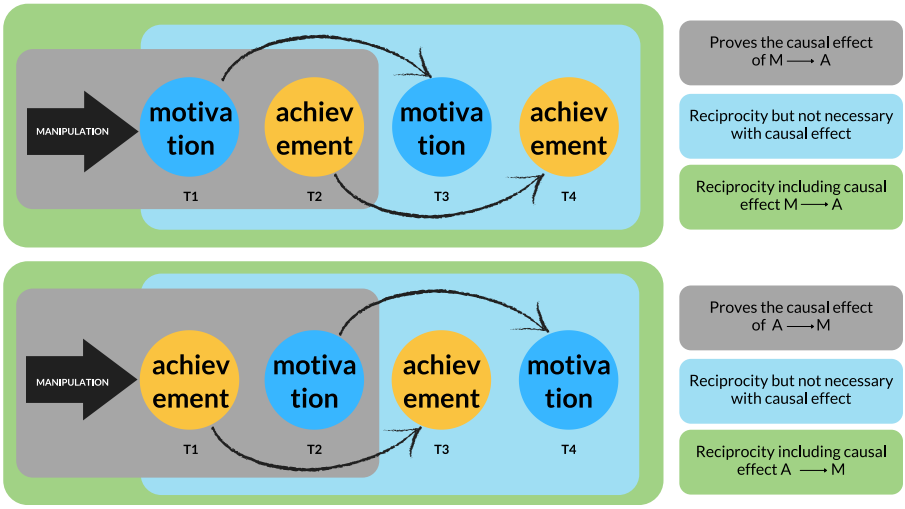

Fig. 2 Representation of three types of study designs that can investigate the relationships between motivation and academic achievement. (1) The gray box shows that to establish that motivation causes academic achievement (top) or vice versa (bottom), experimental manipulation is needed, intervening on the predictor at time point 1, which influences the outcome at time point 2 and so on. The straight thin arrows are the cross-lagged relations and the curved arrows the autoregressive relations. (2) The light blue boxes (top and bottom) illustrate the types of design where reciprocity but not necessary causal effects between motivation and achievement can be established. (3) The green boxes (top and bottom) show the type of design that can investigate both reciprocity and causality between motivation and achievement (i.e., a study where experimental manipulation is included *and* reciprocal relationships are measured). *t* time-point, *M* motivation, *A* achievement

Several studies with high quality and quantity of longitudinal data meet these two preconditions (e.g., Arens et al., 2017; Bossaert et al., 2011; Chamorro-Premuzic et al., 2010; Chen et al., 2013; Collie et al., 2015; Dicke et al., 2018; Grygiel et al., 2017; Hebbecker et al., 2019; Höft & Bernholt, 2019; Marsh et al., 2016, 2018; Miyamoto et al., 2018). In these studies, autoregressive paths (the curved arrows in Fig. 2, which go from measurement of a variable at one time point to the measurement of the same variable at the next time point) and cross-lagged paths (the straight arrows in Fig. 2, which go from measurement of a variable at one time point to the measurement of *a different* variable at a later time point) are found. In other words, autoregressive paths represent the direct effects of variables on themselves over time and cross-lagged paths the direct effects of two variables on each other over time. Such cross-lagged paths show the reciprocity between the variables but not necessarily causality in these relations (Usami et al., 2019). Correlation between different variables, measured at different time points, is a necessary but not sufficient requirement of causality in mutual relations. Establishing causality of reciprocal effects requires the experimental manipulation of at least one of the two variables.

Importantly, to our knowledge, no studies of the mutual relations between motivation and achievement also satisfy the third precondition of causality, that is the *manipulation* of x has an effect on y at a *later* time point, followed by (a) repeated measure(s) of x (and y) (Antonakis et al., 2010). In Fig. 2, manipulation is indicated by the thick arrow. In the upper panel of Fig. 2, the manipulation of motivation affects achievement in the gray (with dash outline) part of the figure. If the manipulation is followed by an alteration of the variables with cross-relations, the

findings would support causality of motivation in reciprocal relations between motivation and achievement. We searched for such studies in meta-analyses of interventions (Harackiewicz et al., 2014; Lazowski & Hulleman, 2016; Sisk et al., 2018), in the latest meta-analysis of longitudinal studies (Huang, 2011) and Scharmer (2020). We encountered two studies that contained both an experimental manipulation of a motivation construct and subsequent multiple, alternate measurements of motivation and performance. Cohen et al. (2009) found that structured writing assignments to prompt African American students to reflect on their personal values (i.e., self-affirmation interventions) resulted in improved academic achievement (GPA), as well as self-perception and an increased rate of remediation, in the following school year for low-achieving African Americans. Yeager et al. (2019), in a large-scale mindset intervention, also had more than one wave of manipulated motivation and measurement of achievement. Although the authors discuss the role of a recursive process Yeager & Walton, 2011), neither of these interventions modeled reciprocal effects between motivation and performance (Cohen et al., 2009; Yeager et al., 2019).

In the lower panel of Fig. 2, the arrow indicates manipulation of achievement. A manipulation of achievement that affects motivation, which is again cross-related to achievement, would support a causal effect of achievement in reciprocal relations between achievement and motivation. However, it is hard to manipulate achievement independently from motivation. For example, manipulations of instruction, modeling, practice, and self-correction may all affect achievement, but they may do so partly by making the material more appealing, raising motivation at the same time or before achievement is raised. New manipulations are needed that raise, for example, perceived performance without raising performance per se, as a way to circumvent such issues. For causal inferences, experiments would ideally include (double-blinded) random assignment, which is possible in the lab but poses important practical problems in the classroom (cf. Savi et al., 2018). In sum, future research with the types of studies that can investigate both reciprocity and causality between motivation and achievement would be highly valuable.

Choice of Appropriate Statistical Models

Although the existence of the reciprocal relationship between motivation and performance is generally agreed upon, there are also empirical works that fail to establish such a relationship (Fraine et al., 2007) or cast doubts on the robustness of the reciprocal effects (Burns et al., 2020; Ehm et al., 2019). Such studies most importantly also point out that the choice of sophisticated statistical models to investigate such relationships can have implications for the conclusion drawn (e.g., Burns et al., 2020; Ehm et al., 2019). Ehm et al. (2019) specifically found that although a cross-lagged panel model (CLPM) supported reciprocal motivation-achievement relations, other models did not—such as the random-intercept CLPM, which Hamaker et al. (2015) showed to be more effective than CLPM in explicitly modeling within- and between-individual changes across time. In addition, as Usami et al. (2019)—in their comprehensive unified framework of longitudinal models—demonstrated, it is important to identify the existence of third time-varying or time invariant variables (such as stable traits) that can have a causal effect on the longitudinal relationship but are yet accounted for in a model. Substantial knowledge about such confounders will help researchers select the correct statistical model. Again, this issue is closely related to the short vs. long cycle of the constructs discussed above.

Alternatives to Self-Reports

Most studies investigating reciprocal relationship between motivation and achievement have measured motivation through questionnaires probing ASC (e.g., the Academic Self-Description Questionnaire by Marsh & O'Neill, 1984). Despite their evident psychometric benefits, self-reports (including questionnaires) of motivation suffer from many inherent caveats. Fulmer and Frijters (2009) list several that are relevant. First of all, questionnaires are subjective and rely on the assumption that motives are consciously accessible, declarative, and communicable to other people, while as discussed above, motivation arises from partially inaccessible and non-declarative cognition and emotions. Students may also differ in their capacity to reliably answer the questions (e.g., consider alexithymia—a psychological trait that is characterized by difficulties with verbalization of one's own emotions and psychological introspection, Lumley et al., 2005). Second, the lack of rigor in the conceptualization of motivation constructs often becomes apparent when using questionnaires (we discuss concrete issues related to ASC in the Different Motivation Constructs section). This is closely related to the Jingle-Jangle Fallacies discussed in Marsh et al. (2003, p. 192). Third, questionnaires might not measure reliably motivation constructs that are not trait-like and subject to temporal and situational fluctuations (e.g., situational interest) (also see our discussion of this point in Time scale of the relations section above). In practice, self-reports cannot be sampled with high frequency during learning (see process-oriented measures below). Fourth, questionnaires are problematic from a developmental perspective because, across age groups, there might be varying factor structures in empirical data. Furthermore, some children may be too young to process some motivation constructs. Finally, self-reports are sensitive to demand characteristics and a tendency to give socially desirable answers (e.g. students who are familiar with the implicit theory of intelligence might tend to report that they endorse a growth mindset, Lüftenegger & Chen, 2017).

Most recent discussions of motivation-achievement interactions emphasize the need for alternative methods to self-report questionnaires. These alternatives include experience sampling, daily diaries, think-aloud protocols, observations, and structured interviews (Eccles & Wigfield, 2020). These alternatives have their strengths, but some limitations remain, such as the subjective nature of these measures and a possible high demand on research participants' cognitive resources when a large number of measures are administered during a session. In addition, some demand frequent small breaks during a task to report internal states, which may interfere with the flow of the task.

Several alternative methods are available to observe and measure motivation or engagement "online" *during* learning, for example by using frequent choices of learners or video observations (Järvenoja et al., 2018). With the development of new technologies, it is now also possible to collect such data longitudinally on a large scale. For example, MathGarden, an online math learning tool, provides access to math learning data of thousands of students. Motivation is indexed by the frequency and length of voluntary, self-initiated practice, and can be linked to learning and performance (Hofman et al., 2018). Other promising process-oriented measures are eye-tracking and facial emotional expressions (D'Mello et al., 2008; Grafsgaard et al., 2014, 2011; Nye et al., 2018; van Amelsvoort & Krahmer, 2009).

Another process-oriented approach uses physiology for high-frequency and non-interfering measures of motivational states. We will briefly discuss the use of autonomic nervous system (ANS) and central nervous system (CNS) measures. ANS techniques can be used to measure *arousal*, which is defined as higher activation of the sympathetic relative to the

parasympathetic system. Motivated and effortful behavior is accompanied by increased arousal, and thus ANS techniques can provide an index of motivation. Popular techniques are electrodermal activity (EDA), electrocardiograms (ECG), and impedance cardiography (ICG). Sympathetic arousal measured with EDA has been associated with emotion, cognition, and attention (Critchley, 2002). Sympathetic arousal can also be measured with pre-ejection period (Tavakolian, 2016)—which is the time in between "the electrical depolarization of the left ventricle and the beginning of the ventricular ejection" (Lanfranchi et al., 2017, p. 145). One shared challenge with EDA and ECG is that arousal is a "fuzzy" construct, meaning many things, yet nothing specific (Mendes, 2016). A common factor that elicits EDA is *subjective salience* or *motivational importance*. Pre-ejection period is often used as an index for *effort mobilization* in studies investigating motivational intensity theory (Brehm & Self, 1989). Suppression of parasympathetic activity, which can be measured as reduction in high frequency heart rate variability, has been associated with effortful control (Spangler & Friedman, 2015) and emotion regulation (Beauchaine, 2015), but a recent meta-analysis supports a more general role in top-down *self-regulation* (Holzman & Bridgett, 2017).

A CNS measure of motivational states can be provided by electroencephalography (EEG). Higher *mental effort/workload* has been associated with attenuated parietal alpha activity (Brouwer et al., 2012, 2014; Fink et al., 2005), higher frontal theta activity (Cavanagh & Frank, 2014; Klimesch, 2012), and a higher theta/alpha ratio. Another useful EEG index of motivation is asymmetrical frontal activity, which has been proposed to index *motivational direction*. Approach and avoidance motivation are respectively related to greater left and right frontal activity (Kelley et al., 2017).

It should be noted that none of these process-oriented measures has currently been established as reliable enough to replace verbal reports. A standard conclusion is that "more research is needed" (Holzman & Bridgett, 2017). A constructive way forward, which Fulmer and Frijters (2009) and Scheiter et al. (2020) strongly advocate, is to triangulate multiple methods, including self-reported and process-oriented measures. Given that physiological measures are relatively new, triangulation can help establish their reliability and validity. For example, EEG could be measured along with behavioral process-oriented task measures of effort. This allows testing whether fluctuations in theta and alpha activities are due to subjective effort mobilization and not due to other processes such as emotional arousal. Such triangulation studies can point the way to reliable online measures of motivation that do not rely exclusively on self-reports.

Measuring Achievement

While achievement is a less-fraught construct than motivation, it still presents its own challenges. First, achievement is nearly always bound to a specific domain, for example mathematics (Arens et al., 2017) or reading skill (Ehm et al., 2019; Sewasew & Koester, 2019). It is unclear whether findings generalize from one domain to others. It is possible that there are quantitative or even qualitative differences between domains in how motivation and achievement interact, for example as a function of the feeling of flow that is or is not associated with performance within the domain.

A second aspect of achievement that may affect results is the type of measurement used. Achievement can be measured using standardized tests and grades in schools (Arens et al., 2017; Marsh et al., 2016), but for example also through teacher or self-assessment (Chamorro-Premuzic et al., 2010). These tend to vary substantially in reliability and validity and yield

different results (e.g., stronger reciprocity for school grades than for test scores; Marsh et al., 2016). Moreover, in longitudinal studies, it is often difficult to assess whether performance at different moments in time truly reflects the same skill. For example, studies of reading skill may assess basic letter decoding skills in a first wave, and complex reading comprehension in the last (Sewasew & Schroeders, 2019). Such changes in tested skills are likely to lead to a lower stability of scores, and skew estimates of change over time. This consideration would speak for designs (discussed above) with shorter periods between measurement waves, where the same measures can be used in different waves.

A third aspect of achievement which may be important is that achievement can be construed as mastery of skills, which usually grows over time, or as performance relative to peers, which by definition cannot grow for all students. Studies typically use raw test scores as a dependent measure to assess this (Huang, 2011; Scharmer, 2020), which reflect mastery of skills. What is communicated to students, on the other hand, tends to be performance relative to peers (e.g., rankings or grades, which tend to be age-normed either explicitly or implicitly). This implies that perceived performance (see Fig. 1) will be based on relative performance, and not on the absolute achievement that researchers tend to study.

Scope of the Theories and Generalizability of Findings

Studies investigating motivation-achievement interactions have often studied the development of these processes separately during childhood, adolescence, and early adulthood. It is therefore unclear whether results can be generalized across developmental stages. Furthermore, as in many subfields of psychology, the majority of research in this area has been conducted in Western, educated, industrialized, rich, and democratic (WEIRD) societies (Henrich et al., 2010), where, for example, rates of schooling are much higher than other places (e.g. the Global South). Here, we outline considerations of generalizability across developmental stages and ethnic and sociocultural settings.

Generalization Across Developmental Stages

Childhood and adolescent development is characterized by rather different trajectories for academic achievement (with a general pattern of improvement with age) than for academic motivation (with a general pattern of decrease during adolescence, as well as diversification in sources of motivation) (Scherrer et al., 2020; Scherrer & Preckel, 2019). As a result, we can speculate that the reciprocal relationships between motivation and achievement will change with age. Below, we first highlight findings on changes in motivation across development, and next describe the consequences of developmental differences on reciprocal relations between motivation and achievement, as a function of age, developmental, and academic stages (such as puberty or school grade).

The way in which value guides goal pursuit transforms profoundly from childhood to adolescence to adulthood (Davidow et al., 2018), and is reflected in changes in reward sensitivity and cognitive control. At the individual level, motivational beliefs related to competence, control and agency, intrinsic and extrinsic motivation, and subjective task value undergo significant changes throughout the lifespan (Wigfield et al., 1998, 2019). Social cognitive accounts often postulate that the development of more sophisticated cognitive capacities with age allows adolescents to improve performance but also to be more aware of their own abilities and those of their peers (Dweck, 2000, Scherrer and Preckel, 2019). As

children go through school, previously held optimistic beliefs on competency become more realistic or even pessimistic (Fredricks & Eccles, 2002; Jacobs et al., 2002; Scherrer & Preckel, 2019; Watt, 2004). A meta-analysis by Scherrer and Preckel (2019) found a small but significant overall decrease in several motivation constructs including academic self-concept, intrinsic motivation, mastery, and performance-approach achievement goals over the course of elementary and secondary school. However, for several other constructs, including self-esteem, academic self-efficacy, and performance-avoidance achievement goals, there was no consistent developmental trend across empirical studies. Overall, this heterogeneity in developmental patterns of various motivation constructs suggests that the reciprocal interactions with achievement may also follow different trajectories across development and still need to be investigated.

Beyond the individual level, social influences on learning and motivation within the family, peer, and school contexts (see Fig. 1) also play a significant role in the changes in motivation and achievement (Nolen & Ward, 2008; Wigfield et al., 1998). Sensitivity to social context continues to develop through childhood and adolescence, transforming through the different school stages (Ladd et al., 2009). Broadly speaking, motivation for academic activities decreases between childhood and adolescence, and motivation reorients toward social and novel situations (Crone & Dahl, 2012). According to the stage-environment fit account, the decline in academic motivation in adolescents is driven by a mismatch between their newly developed needs and their social settings (Scherrer et al., 2020; Scherrer & Preckel, 2019). Specifically, the transition to middle and high schools is usually accompanied by changes in peer relationships, friendship, and teacher-student relationships, an increase in normative and performance-focused evaluation and a decrease in perceived autonomy. Adolescence is especially characterized by heightened social influences on motivation (Casey, 2015): social interactions become increasingly important and peer affiliation motivation peaks (Brown & Larson, 2009).

Indeed, peer relationships show a stronger influence on academic self-concept for seventh graders, compared to fifth graders (Molloy et al., 2011). As children transition into middle school, there is increased competition for grades and typically a larger pool of peers that serve as a reference group (Molloy et al., 2011). During adolescence, same-aged peers in school can motivate academic achievement to a larger extent, and a stronger focus on performance rather than mastery goals is sometimes empirically observed (Maehr & Zusho, 2009, but see Scherrer et al., 2020; Scherrer & Preckel, 2019 where meta-analytic findings point to declines in both mastery and performance goals).

In sum, individual developmental changes in self-concept, self-regulation, social influence, and the values attributed to certain academic goals suggest that reciprocal motivation-achievement relations from one age group cannot be readily generalized to other ages (Marsh & Martin, 2011). Qualitative and quantitative differences in the reciprocal relationship between motivation and achievement thus seem plausible, but the lack of developmentally appropriate measures complicates comparisons across different stages (Fulmer & Frijters, 2009). Populations of different ages have distinct motivation factor structures (Rao & Sachs, 1999) and young children do not yet have the cognitive and memory capacity to process some motivation constructs and contextual references (Fulmer & Frijters, 2009).

Taken together, it is critical to understand how changes in motivation interact with changes in abilities, and affect behavior across different age groups and school career. The literature would greatly benefit from an integration of research across a broader age range, and identifying continuities and discontinuities in the reciprocal relationship between motivation

and performance across development. One way to do this is to leverage accelerated longitudinal designs, with multiple measurements of cohorts with different starting ages and differentiation between multiple motivation constructs (Guay et al., 2003; Marsh & Martin, 2011; Scherrer & Preckel, 2019).

Generalization Across Sociocultural Settings

The reciprocal relationship between motivation and achievement may also take different shapes across contexts, as students belong to different ethnic, gender, socioeconomic (SES), and cultural groups. However, the majority of current research on the reciprocal relations between motivation and academic achievement has suffered from what can be considered a sampling bias problem (Pollet & Saxton, 2019), i.e., conducted using homogenous samples in terms of ethnicity (Marsh & Martin, 2011) and cultural background (Henrich et al., 2010). In the meta-analysis by Valentine et al. (2004), which showed that samples from non-Western countries tended to have larger effect sizes than those from Western countries, there were only four non-Western samples out of a total of 60 samples. In her meta-analysis of Scharmer (2020), 90% of samples were collected in WEIRD countries (Australia, USA, and Western Europe, with fully half using German samples). This is problematic, given that even within WEIRD samples, motivation of students from different groups (e.g., African Americans vs. European Americans) is influenced by different factors, and may contribute differently to their academic achievement (Cohen et al., 2009). Ten years later, the remark of Marsh and Martin (2011) thus still stands that it is premature to conclude that the reciprocal relationship between motivation and achievement is universal.

Demonstrating this across diverse populations is important for three reasons. Firstly, even the same motivation construct might contribute differently to achievement across groups. For example, Chiu and Klassen (2010), using PISA data and a very large and diverse sample (N participant = 88,590, N country = 34), found a positive link between mathematics self-concept and mathematics achievement, but this relationship was moderated by cross-country differences in cultural orientations (specifically, degree of egalitarianism, rigidity in gender roles, aversion to uncertainty). As mentioned above, Sachisthal et al. (2019) also showed that across populations different motivation constructs are central in the network of constructs.

Second, it is not unlikely that different groups have diverging motivation constructs. For instance, general self-concept is conceptualized differently across cultures (Becker et al., 2012; Taras et al., 2010; Vignoles et al., 2016). Thus, the extent to which academic self-concept contributes to a general sense of self likely differs across groups (Hansford & Hattie, 1982). Chen and Wong (2015) also found that Chinese students assigned different meanings to performance-approach and performance-avoidance goals than what is usually found in Western populations. As a result, interventions may need to target different factors in different sociocultural settings.

Finally, there might be culture-dependent or population-specific pathways connecting the relationship between motivation and achievement. For example, culture is likely to have a strong influence on attributional processes (see extensive theoretical discussion in Graham, 2020; empirical data in Chiu & Klassen, 2010) and implicit theory of intelligence (W. W. Chen & Wong, 2015). Chiu and Klassen (2010) found that calibration of mathematics self-concept (i.e., the degree to which judgments of one's competence in a domain accurately reflect actual performance) was positively related to mathematics achievement. However, this

link was significantly stronger in places where the prevailing culture was more egalitarian or more tolerant of uncertainty.

Such findings suggest differences between sociocultural contexts are not just gradual but also likely to be qualitative. This would threaten the generalizability of findings (Henrich et al., 2010). Note that many of the empirical studies cited in this section are non-longitudinal. Reciprocal relationships between motivation and achievement may look different from what we currently know when representative samples are included. It is thus highly relevant for future motivation research to increase ethnic, and other group diversity in their studies. This can be done by better sampling within geographical boundaries (Pollet & Saxton, 2019) and by reaching out to under-researched territories such as in Africa, Middle East, Southeast Asia, Central Asia, and South America.

Diversifying study populations can be tough, but is essential for new understanding of human universals and specifics in motivation. For example, collecting experimental data across countries offers alternative perspectives to experimental set-ups and findings, which subsequently prompt researchers to rethink the constructs of interest and their operationalizations (Vu et al., 2017). Nevertheless, there are innovative solutions to overcome practical difficulties, including collaborating with researchers who reside in places where certain specificity and universality in motivation constructs can be expected (as outlined in some of the examples above) and making use of networks of researchers such as Psychological Science Accelerator to get access to multiple laboratories and populations across the world (https://psysciacc.wordpress.com/).

Discussion and Conclusions

We have summarized theories of motivation and analyzed these specifically with regards to how they conceptualize reciprocal interactions between motivation and achievement. This led to a summary of pathways between motivation and achievement, depicted in Fig. 1. The common denominator between theories suggested reciprocal positive influences of motivation on achievement and vice versa, which has been supported by much previous research. We reviewed the strengths of the underlying data, but also limitations and gaps in the evidence. This led to a research agenda consisting of the following recommendations for future studies on the relationship between motivation and performance: (1) include multiple motivation constructs (on top of ASC), (2) investigate behavioral mediators, (3) consider a network approach, (4) align frequency of measurement to expected change rate in intended constructs and include multiple time scales to better understand influences across time-scales, (5) check whether designs meet the criteria for measuring causal, reciprocal inferences, (6) choose an appropriate statistical model, (7) apply alternatives to self-reports, (8) consider various ways of measuring achievement, and (9) strive for generalization of the findings to various age, ethnic, and sociocultural groups.

One of the hardest problems to solve is the lack of studies that allow for firm causal inferences. Most studies contain sophisticated statistical analyses of longitudinal data. While impressive, the underlying data remains correlational in nature and susceptible to explanations in terms of the presence of a (time-varying or time-invariant) third variable (or variables) that is not accounted for in a model, yet does have a causal effect on the outcomes. Usami et al. (2019) outline three assumptions that need to be checked when making causality inferences in the context of longitudinal designs. These are the assumptions of consistency, of positivity

after controlling for confounders, and of no unobserved confounders (see full the discussion in Usami et al., 2019). In our view, the trickiest is the third assumption: "the relation between x and y must not be explained by other causes"(Antonakis et al., 2010, p. 1087; Usami et al., 2019). There seems to be no way to conclusively rule out the presence of such confounders. Substantial knowledge about potential confounders and their characteristics, and using that knowledge to select the most appropriate cross-lagged model, is necessary.

We argued that the strongest support for causal claims on motivation-achievement relations would be studies manipulating either motivation or achievement at one time point and studying the effects on motivation-achievement interactions across subsequent time points. Such studies do not yet exist to our knowledge. Many studies do show effects of manipulations affecting motivation thereby having an effect on achievement, but these studies have not looked at longitudinal interactions. The other pathway (i.e., achievement → motivation) has not been studied extensively, because of difficulties identifying manipulations that would directly affect achievement but not motivation.

A way to work around this problem is to manipulate perceived achievement, instead of true achievement (our lab study, manuscript in preparation). In this experiment, participants perform a learning task that lasts an hour. Their motivation and achievement are measured at multiple consecutive time points. Halfway through the experiment, a manipulation of perceived feedback is introduced: participants receive rigged feedback that their achievement has dropped to below peer average. The causal relations between motivation and achievement can be examined because manipulated perceived achievement leads to corresponding changes in motivational beliefs, to changes in motivational behaviors and eventually, to changes in actual achievement across multiple consecutive time points. Another example of manipulation of achievement can be found in Bejjani et al. (2019) where they used a feedback manipulation (a competence-threatening IQ score) to study its effect on subsequent motivation and learning.

Furthermore, we have argued that motivation can best be seen as a constellation of highly related, multidimensional constructs, and manipulations of motivation may directly or indirectly influence achievement and vice versa. An innovative method to study the motivation-achievement relationship can be a network approach, where observational and interventional data are used to estimate a causal graph. The idea is that to estimate causal relations, one variable can be manipulated at a time, and its effects on other variables can be observed. The network approach is also beneficial in the classroom context where there are many variables to take into account which cannot be independently manipulated (Yeager & Walton, 2011).

Our discussion of various theories of motivation in education showed how densely motivation and performance are interlinked. They can best be seen as a cycle of mutually reinforcing relations. While a cycle suggests a closed loop, we list several options for outside intervention, which are represented by the gray arrows in Fig. 1. Some of these are well-researched practical interventions, such as autonomy support and training in helpful attributions (Hulleman et al., 2010). Others are excellent avenues for future research. For example, designing how feedback reaches the learner offers opportunities for motivation support. Research has shown how to provide negative feedback in a way that does not lower a learner's motivation (Fong et al., 2019), how peer comparison can be harnessed for motivation (Mumm & Mutlu, 2011), or how feedback can be given without giving away that errors have been made (Narciss & Huth, 2006). It is our impression that this research has so far not reached all classrooms.

In conclusion, this view of a cycle between motivation and achievement, as shown in Fig. 1, has intuitive appeal and fits well with theories of academic motivation. However, empirical

evidence for a cycle is far from complete. The research agenda we have presented contains important challenges for future research aimed at elucidating how motivation and achievement exactly interact, and whether a cycle and a network of constructs are good ways of conceptualizing these interactions. As academic motivation typically drops considerably in adolescence and may be lower for some groups (e.g., through the effects of SES, stereotype threat, and the likes), such evidence is necessary for gaining knowledge on how to best intervene in the cycle, and bring out the best in each student.

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Author Contribution Apart from the first four authors and the last author, the rest of the authors is listed in alphabetical order.

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