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Accessibility
The impact of student misconceptions on student persistence in a MOOC

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Abstract
Massive Online Open Courses (MOOCs) provide opportunities to learn a vast range of subjects. Because MOOCs are open to anyone with computer access and rarely have prerequisite requirements, the range of student backgrounds can be far more varied than in conventional classroom-based courses. Prior studies have shown that misconceptions have a huge impact on students’ learning performance; however, no study has empirically examined the relationship between misconceptions and learning persistence. This study of 12,913 MOOC-takers examines how students’ misconceptions about the upcoming course material affect course completion. Using a survival analysis approach, we found that, controlling for the score in a pre-course test, students holding more misconceptions had a higher dropout rate at the start of the course, an effect that diminished over time. Other student variables were found to have a positive impact on survival that persisted throughout the entire course: U.S. location, higher age, an intention to complete, better English skills, prior familiarity with the subject, motivation to earn a certificate, and score and time spent on the previous problem set (homework). By contrast, student gender, education level, number of previous MOOCs completed, and motivation to participate in online discussion forums did not affect survival.
1 | INTRODUCTION

Since their inception, Massive Online Open Courses (MOOCs) have been projected to revolutionize and democratize higher education (Belanger & Thornton, 2013; Haggard, 2013; Jacobs, 2013; Rice, 2013). Because MOOCs collaborate with top education institutions, charge a low or no fee, bypass admission barriers, and offer a wide range of topics, their “roll-out” has been anticipated as a new model of inclusive education (Dillahunt, Wang, & Teasley, 2014). High volumes of literature have constructed learning theories specifically for the MOOC context and platform (e.g., de Waard et al., 2011; DeBoer et al., 2014; Gasevic, Kovanovic, Joksimovic, & Siemens, 2014; Nawrot & Doucet, 2014). Such learning theories are often applicable or informative also to the offline context (e.g., Grünewald, Meinel, Totschnig, & Willems, 2013; Lee, Linn, Varma, & Liu, 2010; Meek, Blakemore, & Marks, 2017; Núñez, Gené, & Blanco, 2014). In fact, MOOCs provide valuable opportunities to test psychological and educational theories for higher education in general (e.g., Baker, Evans, & Dee, 2016; Bell, 2011; Chudzicki, 2015; Colvin et al., 2014; Joyner, 2017; Mackness, Waite, Roberts, & Lovegrove, 2013; Zhu, Sari, & Lee, 2018) that are difficult or impossible to examine in traditional classrooms, because MOOCs have (a) a large sample, (b) high variation in the sample, (c) a wide range of topics, (d) low stakes in exams and certificates, (e) low cost for any action that participants decide to make, and (f) easy-to-manipulate conditions, such as interface or pedagogy (Anderson, Huttenlocher, Kleinberg, & Leskovec, 2014; Chen et al., 2016; Chudzicki, 2015; Kellogg, 2013; Tomkin & Charlevoix, 2014; Williams & Williams, 2013).

This study examines the relationship between students’ prior misconceptions and students’ retention in the MOOC setting. Although the importance of misconceptions in science education has been stressed in the past three decades (Larkin, 2012; Nixon, Campbell, & Luft, 2016; Posner, Strike, Hewson, & Gertzog, 1982; Sadler, Sonnert, Coyle, Cook-Smith, & Miller, 2013), no study, to the best of our knowledge, has established a link between misconception and retention. The reason is that, in traditional classrooms, the dropout rate is low, and dropping out because of misconceptions (as for other motives) is considered costly and unwise. By contrast, in the MOOC setting, dropout is common and has a low cost. Furthermore, with the large sample size, we have enough power to detect an effect of misconceptions on retention even if the effect size is small.

1.1 | Factors influencing MOOC dropout

Proponents of MOOCs claim that MOOCs not only reduce the cost of human capital training, but also transform higher education toward the development of cultural capital for the satisfaction of lifelong learning (Baker, Evans, Greenberg, & Dee, 2014). Nevertheless, with completion rates ranging only between 5% and 40% (Alraimi, Zo, & Ciganek, 2015;
Breslow et al., 2013; Coffrin, Corrin, de Barba, & Kennedy, 2014; Hollands & Tirthali, 2014; Jordan, 2015), skepticism has been waxing over MOOCs' ability to stay relevant and engage students (Pope, 2014; Zemsky, 2014).

Many studies have investigated the factors influencing dropout in MOOCs. It has been well documented that duration of course activity (He, Bailey, Rubinstein, & Zhang, 2015; Jiang, Williams, Schenke, Warschauer, & O’dowd, 2014; Kloft, Stiehler, Zheng, & Pinkwart, 2014; Peng & Aggarwal, 2015) and students' demographic characteristics, such as gender, age, education, and geographical location, effectively predict dropout. Among the psychological factors, studies have focused on students' motivation (Kizilcec & Halawa, 2015; Xiong et al., 2015), self-regulation (Holder, 2007) and self-efficacy (Abeer & Miri, 2014; Halawa, Greene, & Mitchell, 2014; Nawrot & Doucet, 2014).

A lack of motivation among participants is considered to be the key reason for the high dropout rate (Khalil & Ebner, 2014; Pursel, Zhang, Jablokow, Choi, & Velegol, 2016; Shapiro et al., 2017; Xu & Yang, 2016). Belanger and Thornton (2013) identified distinct motivations of MOOC learners, such as participating for life-long learning, for fun, for convenience, or for the experience. Such motivations further influence student self-regulated engagement patterns, such as being completers, samplers, or no-shows (Hill, 2013; Kizilcec, Piech, & Schneider, 2013; Wilkowski, Deutsch, & Russell, 2014). Recently, scholars have considered motivation to be a component of student self-regulation (Barak, Watted, & Haick, 2016; Magen-Nagar & Cohen, 2017). Ryan and Deci (2000) proposed a self-determination theory (SDT), which posits that learners need a sense of autonomy, aptitude, and relatedness to stay engaged (Durksen, Chu, Ahmad, Radil, & Daniels, 2016; Hartnett, George, & Dron, 2014; Ryan & Deci, 2000). Other researchers have applied the expectancy-value theory to the learning motivation in MOOCs, whereby motivation has been defined as a function of one’s expected chance of success, perceived usefulness of the course and the estimation of the cost (e.g., De Barba, Kennedy, & Ainley, 2016). As shown by Reich (2014), only 22% of those who claimed to be strongly motivated to finish the course actually finished. This suggests that motivation is not constant, but adjusts based on students’ course experiences and time investment (Hone & El Said, 2016). As students have just started enrolling in the course, their inadequate background and competence with the subject matter often reduce their self-efficacy (Shapiro et al., 2017), which in turn downgrades their motivation to complete the course (Sawtelle, Brewe, & Kramer, 2012). Chen, Sonnert, and Sader (2019) have shown a salient MOOC engagement pattern in which learners went to the final assessment when they are still at the beginning of the course. Those with higher prior competence passed the assessment, gained self-efficacy, and stayed in the course; and those who failed the assessment lost their confidence and expedited their dropout.

A great amount of MOOC research has focused on the competence, or readiness, of the students (Breslow et al., 2013; Greene, Oswald, & Pomerantz, 2015; Kizilcec & Halawa, 2015; Milligan, Littlejohn, & Margaryan, 2013). In most of this literature, competence has been measured by self-reported familiarity, prior experience (Breslow et al., 2013; Greene et al., 2015; Kizilcec & Halawa, 2015; Milligan et al., 2013), or a general skill as a proxy (Chen et al., 2019), but most of these measures are problematic when applied to participants with very limited experience, a novice population precisely targeted by entry level MOOCs. Although such students may not have knowledge about the specific course content, they nevertheless hold various preconceptions consolidated from life experience (Fisher, 1985) or convenient model representations (Chen, Schneps, & Sonnert, 2016; Gentner & Wolff, 2000).
1.2 Theories of misconceptions and conceptual change

Developmental psychologists have argued that preconceptions are either critical stepping stones or hurdles to formal learning (Bransford, Brown, & Cocking, 1999; Kennedy, Coffrin, De Barba, & Corrin, 2015; Zimmerman & Schunk, 2011). Erroneous and naïve preconceptions, often termed misconceptions, are not simply wrong knowledge, but involve a “belief system comprised of logically linked sets of propositions” (Fisher, 1985, p. 53) that hamper students’ deep understanding of scientific explanations (Leonard, Kalinowski, & Andrews, 2014; Miller & Brewer, 2010; Posner et al., 1982; Singh, 2007; Spiro, 1988). Conceptual change theories posit that the development of knowledge from misconceptions to scientific understanding goes through multiple stages (Chi, 1992; Chiu, Chou, & Liu, 2002; Eckstein & Shemesh, 1993; Posner et al., 1982), such as dissatisfaction with currently held concepts, encountering new and plausible concepts, and accommodating the new concepts. In the past decades, scholars and practitioners in science education have put great efforts in measuring (Gormally, Brickman, & Lutz, 2012; Liu, Lee, & Linn, 2011; Sadler et al., 2010; Wind & Gale, 2015), tracking (Abraham, Perez, Downey, Herron, & Meir, 2012; DiSessa, 1993; Vosniadou, 1994; Wilson, 2009) and altering (Chen, Pan, Sung, & Chang, 2013; De Posada, 1997; Heddy & Sinatra, 2013; Meichtry, 1993; Vosniadou, 1991) students’ misconceptions.

Although numerous intervention studies have shown effectiveness in correcting student’s misconceptions (Heller, Daehler, Wong, Shinozaka, & Miratrix, 2012; Prince, Vigeant, & Nottis, 2009; Regan, Childs, & Hayes, 2011; Teichert & Stacy, 2002), a common observation was that novice learners holding strong misconceptions often reject interventions at the early stages (Champagne, Gunstone, & Klopfer, 1985; Chi, 2005; Chi, Slotta, & De Leeuw, 1994; Lawson & Weser, 1990), or revert after change (Barnett & Ceci, 2002; Oliver, 2011). The reason for the inertia of misconceptions, as recently argued by scholars, is that intuitive misconceptions cannot be uprooted; they coexist with newly acquired conceptions (Gelman, 2011; Legare & Visala, 2011; Shtulman & Lombrozo, 2016). The coexistence of intuitive misconceptions and scientific explanations has been observed in a wide range of grades, from elementary school (Schneider & Hardy, 2013) and high school (Clark, 2006) to college students (Thorn, Bissinger, Thorn, & Bogner, 2016) and adults (Shtulman, Neal, & Lindquist, 2016). Misconception responses can be elicited by specific contexts (Cavagnetto & Kurtz, 2016; Ha, Lee, & Cha, 2006; Nehm, Beggrow, Opfer, & Ha, 2012) and presentations (Bryce & MacMillan, 2009; Chen, Chudzicki, et al., 2016; Sabella & Redish, 2007), and students have to inhibit their intuition to give scientific explanations (Foisy, Potvin, Riopel, & Masson, 2015; Masson, Potvin, Riopel, & Foisy, 2014).

Knowledge of student misconceptions has long been considered a crucial element of a teacher’s skill (Baumert et al., 2010; Ergönenç, Neumann, & Fischer, 2014; Keller, Neumann, & Fischer, 2017; Sadler et al., 2013). It is an important component of pedagogical content knowledge (PCK), a term created by Shulman (1986) and expanded by generations of researchers in teacher knowledge (e.g., Ball & Bass, 2000; Grossman, 1990; Magnusson, Krajcik, & Borko, 1999). Indeed, Sadler et al. (2013) have shown that students cannot correct their misconceptions by themselves over time, even if their teachers have solid subject matter knowledge, only students whose teachers have knowledge of student misconceptions can achieve conceptual change.

Many studies have shown teachers’ PCK (including knowledge of student’s misconceptions) to predict teachers’ adoption of high quality and effective pedagogies (Hill, Rowan, & Ball, 2005; Peterson, Carpenter, & Fennema, 1989; Windschitl, Thompson, & Braaten, 2011). For example, pedagogies such as category construction (Goldwater & Schalk, 2016), comparison
learning (Alfieri, Nokes-Malach, & Schunn, 2013; Kurtz, Boukrina, & Gentner, 2013; Matlen & Klahr, 2013), simulation (Chen et al., 2013; Chen, Chudzicki, et al., 2016), situated learning (She, 2004), and inquiry-based learning (Prince et al., 2009; Riga, Winterbottom, Harris, & Newby, 2017) have been proven to be effective in addressing student misconceptions. Prior studies also examined the feasibility and effectiveness of adopting such strategies to the online learning environment with the goal of promoting student conceptual change (She & Liao, 2010; Wendt & Rockinson-Szapkiw, 2014).

1.3 Misconceptions and dropout

No study, to the best of our knowledge, has linked misconceptions and student dropout (or retention). In traditional college classroom settings, where the time scale is long (counted in semesters or years) and the dropout penalty is huge (losing tuition, credits, or even the opportunity to earn a degree) (Mortagy, Boghikian-Whitby, & Helou, 2018), dropping out because of a beginner’s psychological frustration during mental paradigm shift may be considered extremely costly. Studies have shown that the frustration induced by cognitive and emotional conflict may lead to students’ psychological burnout—exhaustion or cynicism (Khalaj & Savoji, 2018; Olwage & Mostert, 2014; Salanova, Schaufeli, Martínez, & Bresó, 2010), or disengagement (Gan, Shang, & Zhang, 2007; Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1986). Burnout, however, has been found to materialize as dropout only when the frustration becomes severe (Bask & Salmela-Aro, 2013; Duque, 2014; Ensminger & Slusarcick, 1992). Specifically, Salanova et al. (2010) showed that students’ burnout was strongly predicted by a classroom setting that combined the presence of learning obstacles with the absence of facilitators—an environment similar to the traditional MOOC setting. Moreover, in the MOOC setting, where the time scale for taking the course is short (ranging between weeks and hours, in the extreme), and the dropout penalty is minimal, a moment of cognitive conflict may justify dropping out of the course.

Thus, though MOOCs differ from offline learning contexts, they qualify as a “strategic research site” (Merton, 1987) for three reasons. First, MOOCs an expanding and ever more important format for science education. Second, they provide the opportunity to examine how students’ retention is affected by their prior misconceptions, an effect that is otherwise too small to detect in traditional classroom settings. This, in turn, facilitates a more comprehensive understanding of the effects of misconceptions. Third, it may allow inferences for the domains of out-of-school-time and informal science learning where dropout is similarly easy, but where learners’ characteristics and behaviors can rarely be tracked in the comprehensive way that MOOCs afford.

Although no prior study, to the best of our knowledge, has empirically examined the relationship between misconceptions and retention, science learning theories have implied a relationship between the two. In the following, we examine this pattern through the theoretical perspectives of cognitive conflict theory and expectancy-value theory.

1.4 Cognitive conflict theory

The coexistence of misconceptions and newly acquired scientific knowledge may evoke cognitive conflict (Kang, Scharmann, Kang, & Noh, 2010; Labobar, Setyosari, Degeng, & Dasna, 2015; Lee & Byun, 2012; Ramsburg & Ohlsson, 2016; Swan, 2005; Wartono & Putirulan, 2018;
Wyrasti, Sa'dijah, As'ari, & Sulandra, 2018). By definition, cognitive conflict is “a perceptual state in which one notices the discrepancy between one’s cognitive structure and the environment” (Lee et al., 2003, p.585). The cognitive conflict theory was the successor of Piaget’s (1967) equilibration theory and Festinger’s (1957) cognitive dissonance theory, and became a component of the conceptual change theories in education (Hewson & Hewson, 1984).

Many studies have investigated how misconceptions evoked cognitive conflict, related to student-teacher dynamics (Larkin, 2012; Nixon et al., 2016; Sadler et al., 2013). Traditionally, researchers assumed that learners hold coherent and theory-like mental models, like scientists would, which implied that learners should first be dissatisfied with their existing conceptions in order to be motivated to acquire new knowledge and generate more plausible and coherent theories—a concept that lies at the core of the classical cognitive conflict approach (e.g., Hewson & Thorley, 1989; Ioannides & Vosniadou, 2002). Recent studies have presented evidence that students do not always hold coherent mental models, but rather scattered elements from multiple perspectives because for them, as novices, their responses are highly context-dependent (Bao & Redish, 2006). This finding gave rise to more gradual and contextualized pedagogies—known as the cognitive perturbation approach (Dega, Kriek, & Mogese, 2013; Li, Law, & Lui, 2006; Özdemir & Clark, 2007). Overall, both approaches have stressed that cognitive conflict is a valuable window for motivating inquiry for deep understanding (Appleton, 2008; Chow & Treagust, 2013; Delgado & Lucero, 2015; Halim & Meerah, 2002; Harmon-Jones, Amodio, & Harmon-Jones, 2009; Larkin, 2012; Sadler et al., 2013; Treagust & Duit, 2008; Van Driel, Verloop, & De Vos, 1998).

Although cognitive conflict has often been considered to be a valuable opportunity and premise for conceptual change, it inevitably frustrates the students (Dega et al., 2013). Cognitive conflict often occurs together with (De Dreu & Weingart, 2003; Simons & Peterson, 2000), and even provokes (Kellermanns & Floyd, 2005; Mooney, Holahan, & Amason, 2007), affective (emotional) conflict. This problem has been raised as early as 1979 by Carl Frankenstein, who worried that a lengthy experience with cognitive conflict may increase students’ frustration so much so that they halt conflict resolution. This is especially true for low academic achieving students. Zohar and Aharon-Kravetsky (2005) showed that cognitive-conflict-inducing pedagogy was effective only for high achieving students and hindered the progress of low achieving students.

This dual function of cognitive conflict is also discussed in the framework of threshold concepts, which are “bottle-neck” or “gate-keeping” concepts in one’s knowledge progression that open a new perspective that was previously inaccessible and invite the learners to irreversibly transform their mental model (Meyer & Land, 2006). However, when learners perceive the threshold concepts to be counter-intuitive, intellectually absurd, and emotionally frustrating, they may revert back to, and get stuck with, their original misconceptions by alienating the new concepts, which was what Perkins (1999, 2006) referred to as troublesome knowledge.

A common assumption embedded in the abovementioned conceptual change literature is that students would keep learning in the course regardless of whether they were retaining or revising their intuitive misconceptions. No component in the conceptual change theories has explicitly proposed or modeled the possibility that students with strong misconceptions are likely to become motivated, or resigned, in the early stages of an intervention when they encounter cognitive conflict. As argued above, the conceptions that coexist in a student’s mind are often conflicting beliefs (Lawson, 1988; Potvin & Cyr, 2017; Potvin, Sauriol, & Riopel, 2015; Smith, 1994). Students who hold strong and systematic misconceptions tend to
find the new knowledge system taught to them in formal learning settings to be counterintuitive (Guzzetti, 2000).

It is possible that learners are motivated to resolve this cognitive conflict by learning more course content (as reviewed earlier, cognitive conflict motivates students to question and to learn), which would predict longer retention for learners with more misconceptions than for learners with fewer misconceptions (provided that their total amount of subject matter knowledge are the same). For example, in a hypothetical scenario, two learners respond to 10 subject-matter questions before taking a (MOOC) course and both answered 5 questions wrong. If out of the 5 wrong answers, learner A gave 3 misconception responses, and learner B gave 0 misconception responses, it is predicted that learner A would have longer retention in the course than would learner B; or conversely, that learner B would dropout earlier from the course than would learner A, because learner A would be more intrigued to learn more to resolve the cognitive conflict.

However, despite of the possibility of cognitive-conflict-induced curiosity, learners may also need extra efforts to inhibit their intuitions (Foisy et al., 2015; Masson et al., 2014) and to restructure their mental models (Gadgil, Nokes-Malach, & Chi, 2012; She, 2004; Vosniadou, 1991). The mismatch between one's intuition and the taught subject matter knowledge, and the extra efforts required to reconcile the mismatch, may frustrate students and increase their resignation. Such resignation may explain why misconceptions are stubborn, and many intervention efforts, futile. It may also predict that learners with more misconceptions have lower retention than do learners with fewer misconceptions. According to this hypothesis, learner A is predicted to drop out earlier than learner B in the above hypothetical scenario.

Thus, from cognitive conflict theory, one might deduce opposing hypotheses about the effect of misconception on retention. It might be positive or negative. In the online learning environment, in particular, it is difficult for teachers to update their knowledge of students' misconceptions interactively, and also difficult for them to monitor students' cognitive conflict. As explained above, a lack of knowledge of student misconception among teachers, combined with a lengthy cognitive conflict experienced by students, may not effectively promote conceptual change, but may exacerbate students' struggle and resignation. Therefore, we were more inclined to hypothesize that misconceptions have negative effects on retention. It is of theoretical importance to empirically examine the effects and to discern between the two mutually opposite hypothesis. Moreover, this is not a problem that only concerns the online learning environment. As research has shown (Pintrich, Marx, & Boyle, 1993; Zohar & Aharon-Kravetsky, 2005), any classroom in which the teacher is not sensitive to students' misconceptions or cognitive conflict may go through the same struggle, but that struggle may not manifest itself as openly as in the MOOCs context.

Cognitive conflict theory also implies that the effect of misconception on retention should diminish over time as the misconceptions are resolved or inhibited. As learners with many misconceptions update their mental model, and the course content appears less counter-intuitive, intellectually absurd or emotionally frustrating, they are expected to persist in the rest of the course on equal footing with those learners with initially fewer misconceptions.

1.5 Expectancy-value theory

One of the most-cited theories in examining dropout behavior is expectancy-value theory. It has been widely applied to explain why people drop out from careers (e.g., Luscombe, Lewis, & Biggs,
Developed by Atkinson (1957) and through multiple generations of modification (e.g., Eccles & Wigfield, 1995), the expectancy-value theory posits one's motivation in a task to be a function of (a) the expectancy of success (based on an estimation of the task difficulty), (b) the utility value of task completion, and (c) the estimated cost (money, effort or time) of achieving the expected success.

In Atkinson's original version of the expectancy-value theory, expectancy was tied to the success rate in the task that an individual has experienced in the past. Other researchers theorized that expectancy was formulated not only based on prior success but also on the evaluation of the task difficulty and one's self-competence (e.g., Eccles & Wigfield, 1995). One crucial assumption behind both formulations of expectancy was that people know the success and failure of their past experience or, in the context of knowledge acquisition, have an approximately accurate evaluation of what they know or do not know. Nevertheless, the fact that many elements of the existing knowledge people hold are misconceptions that are confidently believed to be true (and successful in explaining a lot of the past experience) seriously challenged the assumption that one can accurately estimate the expectancy of success, or the assumption that people in general have about the same insight into their past success rate, their current competence and their future performance. A person who answers 5 questions wrong and gives 0 misconception responses may be more aware of his/her lack of subject matter knowledge than a person who answers 5 questions wrong, but gives 3 misconception responses. In other words, learners with more misconceptions may be overly optimistic about their past success and their expectancy of success. This optimism may be a buffer that prevents them from dropping early out of a MOOC, as prior studies have shown that over-optimism is preferable to over-pessimism in helping learners persist in science subjects (Bench, Lench, Miner, Flores, & Liew, 2015; Watt, 2010). However, once the courses kick off, learners holding more misconceptions may soon perceive stronger mismatch between their expectancy and the actual task difficulty than may those who have similar amount of subject matter knowledge, but fewer misconceptions. This mismatch may inform the learners of their miscalculation of the expectancy and cast doubt on their self-concept and self-efficacy, which may negatively influence their course retention. Thus, expectancy-value theory also implies two opposite hypotheses about the relationship between misconception and retention: over-optimism may have a positive effect on retention; or the disturbed expectancy may have a negative effect on retention. The expectancy-value theory also implies that once a learner adjusts his/her expectation over time, the effect of misconception should diminish gradually.

1.6 | Hypothesis

We hypothesized that holding misconceptions may be negatively or positively associated with retention in the initial stages of a MOOC, but not in intermediate or later stages. The reasoning was that the mismatch should be most strongly felt when students carrying misconceptions were first introduced to the new and scientific knowledge system, but that, as the students adapted to the new system, they should persist equally well as students with fewer prior misconceptions. This should manifest as an interaction effect of misconception and course milestones on the probability of dropout at a corresponding milestone. This hypothesis was supported by earlier work by Chen et al. (2019) that showed precomputational thinking skills, a measure of logical and algorithmic thinking styles prevalent in computer science, to have a
positive impact on students' retention in an introduction to computer programming MOOC. However, that effect diminished to non-significance over the course milestones. The cited study, however, measured competence, using a general skill as a proxy; it did not measure misconceptions. In our current study, we will extend our understanding of MOOC retention by connecting it specifically to students' misconceptions.

In this study, we used year 2017 data about students' characteristics, activities, and performance in the MOOC Super-Earths and Life (SPU30x), which was a HarvardX MOOC, available on the edX platform. The course was taught by a professor of astronomy. The course used astronomy and space science concepts to discuss the discovery of exoplanets (planets around other stars) that could be favorable for life.

The course has been offered on the edX platform since 2015, each year the teaching team makes very minor revisions to the course content. Although the teaching team was not oblivious of the notion of misconceptions, it did not intentionally address students' misconceptions in the design of the course content and pedagogy. The principal investigators of this study collaborated with the teaching team in data collection, but the investigators and the teaching team were independent from each other. Thus, SPU30X should be considered a regular astronomy and space science course, not a special treatment for astronomical misconceptions.

The major chapters of the course included (a) reviewing the Earth in the solar system, with an emphasis on the spatial, chemical, and climate conditions that make life possible (4 sessions); (b) measuring the distance to the planets and stars, measuring their mass and size, and making inferences about their formation (4 sessions), (c) understanding the types of exoplanets, plate tectonics, and atmosphere on exoplanets (5 sessions), and (d) detecting signals of life, using telescope and spectrometer, and wrap-up (5 sessions). If each session is considered a milestone, there were 18 milestones.

Because it has been well documented that misconceptions about scale (e.g., Miller & Brewer, 2010), spectroscopy (e.g., Ivanjek, Shaffer, McDermott, Planinic, & Veza, 2015), energy (e.g., Zeilik, Schau, & Mattern, 1998), and about the complexity required in scientific models (i.e., students failing to hold multiple factors [vs. a single factor] in their mental model) (Prather, Slater, & Offerdahl, 2002) are crucial threshold concepts to astronomy learning, we adopted misconception-driven test items to probe learners' understanding in these domains.

1.7 | Learning astronomy

When the journal Science asked about the most exciting open questions of science, “Are we alone” ranked at the top of the list (Kennedy, 2005), which is also one of the few science questions that are equally appealing to both genders (Krstovic, Brown, Chacko, & Trinh, 2008). The search of exoplanets and alien life forms is an ideal topic that attracts learners who wish to learn out of curiosity (social capital) rather than for professional skills (human capital). Yet, such a topic connects to core and crosscutting concepts from multiple disciplines (Gould, Sunbury, & Dussault, 2014; Rijsdijk, 2000). Thus, science education practitioners have created many resources and curricula that teach about exoplanets online, and considered it to be one of the best practices of online learning for the promotion of science literacy of the public (Gould, Dussault, & Sadler, 2006; Gould, Sunbury, & Krumhansl, 2012).

Although astronomy is fascinating to a broad population, it is also one of the science subjects that people most rapidly lose interest and do not pursue at a deeper level of understanding (Bergstrom, Sadler, & Sonnert, 2016; Sadler, Sonnert, Hazari, & Tai, 2012). Studies have shown that learners often prefer to stay at a superficial and misconceptual understanding of astronomy
(Bailey & Slater, 2003; Snyder, 2000) even if they were introduced to scientifically accurate conceptions (Champagne et al., 1985; Chi, 2005; Gilbert, 2004). From a learning progression point of view, the understanding of the complexity of astronomy depends on grasping steppingstone concepts (also known as threshold concepts) and overcoming intuitive misconceptions (also known as troublesome concepts). Sadler (1992, 1996) showed that grade 8–12 students failed to understand the reason for day and night because they believed that the Earth orbits the Sun in a day. Further, with a confusion about orbiting and spinning, it is nearly impossible for learners to understand the galactic rotation, using spectroscopy. For another example, once learners understand the scales of the distances between Earth, the planets, and the stars, astrology would not make sense to them (Sadler, 1996). Conversely, if students do not resolve scale-related misconceptions, they will, in addition, remain troubled in grasping many other concepts, such as the change of the seasons (Trumper, 2001) and the phases of the Moon (Plummer, 2006), which all rely on understanding scale (Fanetti, 2001; Miller & Brewer, 2010). Chen, Chudzicki, et al. (2016) have shown that, when astronomy learners switch from scale-accurate models to scale-exaggerated models, they can keep acquiring new knowledge without developing scale-exaggeration-related misconceptions; however, when learners switch from scale-exaggerated models to scale-accurate models, the misconceptions associated with the scale exaggeration remain strong, and learners do not acquire any new knowledge from inspecting the new and more accurate models, as if the learners mentally shutdown (or burnout) from receiving more accurate, yet cognitive-load-heavy information once they consolidate with the attractive misconceptions.

The abovementioned studies and others that showed that misconceptions are tenacious only argued that misconceptions can reduce learning, but did not contemplate the possibility that learners mentally stopped learning altogether when they found the new knowledge to be incongruent with their existing perspectives, because they were forced to sit in the classrooms. In a MOOC setting, students can voluntarily quit whenever they want, which enabled us to explore the relationship between preexisting misconceptions and actually quitting learning. This study of the relationship between misconceptions and retention may inform about how learners withdraw from further knowledge acquisition under the influence of preexisting misconceptions. A study of such a topic may be valuable to the field of astronomy education, and also to the broader field of science education, and especially in the domain of out-of-school-time and informal science learning.

The advantage of choosing an astronomy topic for this study was that (a) it has been well studied that novices have naïve misconceptions about basic astronomy concepts, such as the change of seasons, the phases of the moon, or cosmic scales (Ashmann, 2012; Barrier, 2010; Comins, 1998; Turkmen, 2017; Zeilik & Morris, 2003); (b) it is known that misconceptions about such fundamental concepts in astronomy have long standing deleterious effects on students’ learning of space science in formal classes (Trumper, 2001; Zeilik et al., 1998); and (c) there are well developed misconceptions-oriented test banks in astronomy for novices, tests that have good psychometric properties (e.g., Eryilmaz, 2002; Sadler et al., 2013) and they are public available (Sadler et al., 2010). Therefore, SPU30X is not only a topic that is appealing to a broad population, but also presented a subject field in which the effect of misconceptions is strong, well-documented, and convenient to replicate.

1.8 | Research question

Thus, our research question was whether the number of student misconceptions in the space science background knowledge test (misconception score) from the presurvey (pretest) was
associated with the dropout rate at a given milestone, and if its effect interacts with the number of milestones that have been completed. We hypothesized an initial effect (increasing the dropout rate) that would attenuate over the course of the MOOC. We adopted a survival analysis approach to investigate this relationship. In this model, we controlled for the total score in the pretest as well as other covariates, such as students’ demographic information, motivation, prior experience, the time elapsed since passing the most recent previous milestone, and their grade in the problem set (pset) of the most recent previous milestone (as explained below in the variable section).

2  |  METHOD

2.1  |  Sample and baseline variables

Thirty thousand six hundred ninety-six individuals registered for the MOOC SPU30X on edX; however, only 12,913 of those registered came back to the course and finished the pre-survey, which was a prerequisite to gain access to the course material. Nine hundred and thirty-eight of those finished the pre-survey did not continue viewing the course, which reduced our analytical sample to 11,966. In this article, we considered those who finished the pre-survey as formal enrollees and applied statistical analysis only to the formal enrollees. Around 9% of the participants were so-called “samplers,” meaning they skipped at least one milestone in their sequence (e.g., someone could complete problem sets [psets]1, 2, and 5, and then drop out, skipping pset-3 and pset-4). This irregular pattern is not suitable for a survival analysis framework and was investigated in a separate study. Here, we excluded the irregular participants, which reduced our sample size to 10,014.

2.2  |  Presurvey

Among the 10,014 enrollees, 40% were male, 60% were female. The mean age was 29.5 years (SD = 11.2), 63% were living in a country outside of the USA. Thirty-four percent of the enrollees were concurrently going to school, and 53% had a college or higher degree. On average, enrollees had registered in 1.6 MOOCs and had completed 1.2 MOOCs prior to this MOOC enrollment. Familiarity with the topic of the course was reported by 23%; a somewhat or strong motivation to earn certification by 52%; and a somewhat or strong motivation to participate in the online forum by 26%. Eighty-eight percent reported being proficient or fluent in English.

The presurvey included a space science background knowledge test (the pretest) drawn from items deemed relevant to the concepts covered in the course and derived from the Astronomy and Space Science Concept Inventory Project (Sadler et al., 2010). The test items were multiple-choice questions about space-related science that were chosen from the existing validated test bank that covered knowledge required by the National Science Education Standards (National Research Council, 1996) and the American Association for the Advancement of Science Benchmarks for Science Literacy (Project 2061, 2001). The development of the items and associated answer choices was guided by existing research on learning trajectories of key concepts in astronomy and space science and by the way these concepts were represented in national standards (Plummer & Krajcik, 2010; Plummer & Maynard, 2014; Sadler, 1996).
Each test item contained four choices from which students were to select, with one correct choice, one attractive misconception choice (chosen by more than 50% of the participants in the large scale field test who answered the item incorrectly), and three plain wrong (or less distracting) answers that did not reflect popular misconceptions. Because each item has one misconception as a distractor, this type of test is known as a misconception-driven test. The development of the items went through several key steps, including (a) literature review, (b) writing draft items, (c) expert validation, (d) pilot test, (e) large scale field test, (f) psychometric analysis, (g) constructing final test items, and (h) practice testing the final test items. The complete inventory (211 items) has a Cronbach internal reliability of 0.85. In the field test carried out in 2003, high school students (the target population who the items were designed for) correctly answered 50% of the items, on average. The corresponding percentages were 65% for college students and higher than 80% for school science teachers (see Sadler et al., 2010, for detailed procedures of test development and for psychometric properties of the items).

The pretest used in this study comprised 12 items (see Appendix). The average sum score for correct answers was 7.95 (standard deviation: 2.28), and the average misconception score was 2.64 (standard deviation: 1.75). Below is an example item from the pretest. It probes for concepts about the source of energy and the scale of energy produced by the stars. The correct answer is (c), and the most common misconception is (d), which is rooted in combustion ideas, which, in turn, lead to failures in estimating the magnitude of energy produced by stars.

An astronomer would say that most stars produce energy in the same way as:

a. a wood fire.
b. molten rock.
c. a hydrogen bomb.
d. a chemical reaction between two gases.
e. a welding torch.

Regarding MOOC performance, the course contained 18 milestones, and each milestone ended with a problem set (pset). On average, participants completed 7.53 problem psets out of the total number of 18 psets. Three thousand fifty-one (23% of all) participants finished all 18 psets, in line with the completion rate in previous years (~20%). On average, students spent 47 min on each milestone session (SD = 39). The questions included in the psets simply revisited the course content; they were very easy, with an average difficulty of 0.1 (only 10% learners gave wrong answers). Thus, the psets mostly served as a check point, not necessarily probing learners’ advanced knowledge.

2.3 Analysis

To model dropout rate at a given milestone as a function of predictors (such as pretest, motivation, etc.), we adopted a survival analysis approach. A survival analysis involves three basic terms: event, time, and censoring. In our case, event is student dropout (1 = dropout; 0 = completion) at a given milestone, time is the course milestone, and censoring is if a subject does not experience dropout during the whole MOOC period (in other words, the student completes all milestones). Survival analysis is analogous to logistic regression: the dropout event is a binary outcome variable; milestone and other covariates are predictors; and the model parameters can be interrelated in the same fashion as a logistic regression.
As basic steps for survival analysis (see Singer & Willett, 2003), we first calculated the hazard for each milestone period. The hazard function represents the proportion of each milestone interval set that dropped out during that interval:

\[ h(m_{ij}) = \Pr(M_i = j | M_i \geq j) \]

where \( h(m_{ij}) \) is known as the population discrete-time hazard. \( M_i \) represents the milestone period \( j \) when individual \( i \) experiences the dropout event (e.g., for a student who drops out at the third milestone, \( M_i = 3 \)). The hazard function denotes that the probability that the dropout event will occur at a certain milestone \( j \) for student \( i \) is conditional on student \( i \) not experiencing the dropout event at any time prior to \( j \). Table 1 showed the life table for the observed sample, the survival, cumulative failure and hazard function at each milestone interval.

Next, we used a logit link function to link the hazard to a linear specification of predictors, similar to a logistic regression:

\[ \logit h(m_{ij}) = \alpha_1 + \beta_1 M_{ij} + \beta_2 M_{ij}^2 + \beta_3 X_{1ij} + \beta_4 U_{1ij} + \beta_5 M_{ij} \times X_{2ij} \]

In this function, \( M_i \) and \( M_i^2 \) together represent the linear and quadratic main effect of a milestone. There are multiple possible specifications of the main effect of a milestone, such as treating milestones as dummies (if the hazard function has an irregular form) or as a linear main effect (if the hazard function is close to a linear line). Upon inspection of the logit hazard function, we decided that a quadratic specification would parsimoniously and accurately reflect the hazard function in our case. Predictors of interests in this model are the \( X \) variables and \( U \) variables. \( X \) variables are time invariant variables; they include students' age, gender, motivation, familiarity, pretest score, English fluency, foreign status, etc. (see Table 1 for the full list of variables). Such variables were only measured in the initial questionnaire (milestone 1). They reflected students' initial status and were considered time invariant. \( U \) variables are time-varying predictors. In our case, there were three time-varying predictors, which were the score in the previous pset (variable name: \( pscore \)), and time spent in the previous milestone (variable name: \( active\_time \)). We used \( pscore \) and \( active\_time \) as a proxy for students' performance and engagement, but the validity of such usage was arguable. Both variables were time-lagged by one milestone from the dropout event to be predicted. One reason was that when participants dropped at a milestone, their pset scores would be missing, and their \( active\_times \) in the milestone of the dropout event would be extremely low or missing.

The time-lagged model allowed us to predict the odds of dropout in the upcoming milestone, based on the performance in the most recent active milestone. The course contained four chapters; therefore, there were three occasions for new-chapter = 1, respectively at milestone 5, 9, and 14, whereas new-chapter = 0 for other milestones. Thus, new-chapter could be considered as a discrete time-varying predictor. If we found the estimated coefficient of new-chapter to be positive and statistically significant, we would conclude that the dropout event was more likely to happen after the end of a chapter and before the beginning of a new chapter.

The parameters (\( \beta \)s and \( \gamma \)s) associated with the \( X \)s and \( U \)s stand for the shift in the baseline logit hazard function (as depicted by the main effect of a milestone), corresponding to unit differences in the associated predictors. In other words, the logit hazard function of students with different \( X \) or \( U \) values shift up and down, but the shape of the function should be identical as
it is determined by the main effect of a milestone when we do not take into consideration the interaction terms. We also considered interaction terms between predictors and milestones. This allowed different students to have different shapes of the logit hazard function, depending on their Xs and Us. When two groups (categorized by a predictor of interest such as gender) have converging logit hazard curves, it means the two groups have a larger difference in dropout rates at the beginning, and that this difference decreases over time (i.e., the effect of the group predictor attenuates). If the logit hazard curves diverge between two groups, it means the group differences increase over time. We used a post-GLM test to examine if and at which milestone the two logit hazard curves converge or diverge.

### RESULTS

Table 2 presents the parameters for the fitted model. The model used quartic terms to define the relationship between dropout and milestone. The predictors included time constant variables, such as age, gender, prior familiarity, which were collected only once (in the presurvey) and were considered to be invariant over time. The model also included time-varying predictors, such as students’ performance in the psets and time spent on the milestone, which varied at each milestone. For ease of interpretation, we converted the estimated parameters of the final model to odds ratios by exponentiation and then to marginal probabilities (the change of the

| Interval 1 | Number counts | Survival function | Cumulative failure function | Hazard function |
|-----------|---------------|--------------------|-----------------------------|----------------|
| From To   | Beginning Dropout Prob. SE | Prob. SE | Prob. SE |
| 1 2       | 10,014 2,347 0.766 0.004 | 0.234 0.004 | 0.266 0.005 |
| 2 3       | 7,667 1,893 0.577 0.005 | 0.423 0.005 | 0.282 0.006 |
| 3 4       | 5,774 848 0.492 0.005 | 0.508 0.005 | 0.159 0.005 |
| 4 5       | 4,926 268 0.465 0.005 | 0.535 0.005 | 0.056 0.003 |
| 5 6       | 4,658 282 0.437 0.005 | 0.563 0.005 | 0.062 0.004 |
| 6 7       | 4,376 159 0.421 0.005 | 0.579 0.005 | 0.037 0.003 |
| 7 8       | 4,217 223 0.399 0.005 | 0.601 0.005 | 0.054 0.004 |
| 8 9       | 3,994 146 0.384 0.005 | 0.616 0.005 | 0.037 0.003 |
| 9 10      | 3,848 252 0.359 0.005 | 0.641 0.005 | 0.068 0.004 |
| 10 11     | 3,596 121 0.347 0.005 | 0.653 0.005 | 0.034 0.003 |
| 11 12     | 3,475 28 0.344 0.005 | 0.656 0.005 | 0.008 0.002 |
| 12 13     | 3,447 54 0.339 0.005 | 0.661 0.005 | 0.016 0.002 |
| 13 14     | 3,393 87 0.330 0.005 | 0.670 0.005 | 0.026 0.003 |
| 14 15     | 3,306 119 0.318 0.005 | 0.682 0.005 | 0.037 0.003 |
| 15 16     | 3,187 27 0.316 0.005 | 0.684 0.005 | 0.009 0.002 |
| 16 17     | 3,160 19 0.314 0.005 | 0.686 0.005 | 0.006 0.001 |
| 17 18     | 3,141 90 0.296 0.005 | 0.704 0.005 | 0.057 0.006 |
The probability of dropping out corresponding to a one-unit change in a specific covariate, provided that other covariates are held constant at their means and that the milestone is held at milestone 1.

Interpretation of the parameters is analogous to the interpretation of a logistic model: $\beta$ shows the amount of change in logit hazard associated to one unit of change in the predictor, and the logit hazard can be converted to an odds ratio. For example, $\beta_{\text{located in US}} = 0.26$, which shows that the logit hazard for participants located in the US was larger by 0.26 than the logit hazard for participants located outside of the US, controlling for other covariates. This could further translate to an odds ratio of 1.30 ($e^{0.26} = 1.30$), which means that the odds of dropping out for a US-local participant were 1.30 times as high as the odds of dropping out for an outside-of-the-US participant. Controlling the other covariates at their means and assuming milestone = 1 and new-chapter = 0, we calculate the marginal probability (comparing probability when located_in_US = 1 versus located_in_US = 0) of dropout was 0.063, which means that, at milestone 1, the probability of a US-local student dropping out was 6.3% higher than that of an outside-of-the-US student, if every other covariate was controlled at its mean. This difference was statistically significant.

Similarly, students who reported having stronger intentions to earn a certificate, students from outside of the United States, students of older age, students who reported being more familiar with astronomy, and students who reported having better English skills, had lower odds of dropout at each milestone, compared with their counterparts in the respective reference categories. These predictors did not have an interaction effect with milestones, which means

**TABLE 2** Survival analysis predicting dropout from MOOC Super-Earths and Life

|                          | Coefficient | (SE)      | Odds ratio | Marginal Prob |
|--------------------------|-------------|-----------|------------|---------------|
| (Intercept)              | -0.043      | (0.249)   | 0.827      |               |
| Milestone                | -0.619      | (0.035)** | 0.512      |               |
| Milestone$^2$            | 0.025       | (0.002)** | 1.021      |               |
| Misconcept score         | 0.117       | (0.029)** | 1.124      | 0.025         |
| Pretest score            | -0.061      | (0.021)** | 0.721      | -0.058        |
| Female                   | -0.015      | (0.055)   | 0.984      | -0.003        |
| Age                      | -0.104      | (0.029)** | 0.914      | -0.018        |
| Education                | -0.018      | (0.027)   | 0.981      | -0.004        |
| Located in the US        | 0.260       | (0.056)** | 1.297      | 0.063         |
| MOOCs completed          | -0.048      | (0.027)   | 0.949      | -0.011        |
| Familiarity              | -0.064      | (0.028)   | 0.945      | -0.012        |
| Motivated to earn certificate | -0.135    | (0.029)** | 0.892      | -0.023        |
| Motivated to disc in forum| 0.042      | (0.029)   | 1.058      | 0.012         |
| English skill            | -0.098      | (0.026)** | 0.919      | -0.017        |
| First unit of a chapter  | 0.342       | (0.100)** | 1.408      | 0.076         |
| Time spent in previous milestone (active_time) | -0.299 | (0.038)** | 0.745      | -0.058        |
| Score in previous pset (pscore) | -0.318 | (0.029)** | 0.727      | -0.063        |
| Milestone × Misconcept score | -0.018 | (0.005)** | 0.982      | -0.004        |

Note: *p < .05; **p < .01; ***p < .001, after false discovery rate (FDR) adjustment.
changes to these predictors were associated with the elevation of the fitted line (or curve) of the logit hazard curve but did not change the slope of the line (or the shape of the curve).

By contrast, there was a significant interaction effect between misconception score and the milestones: students who had a higher misconception score—controlling for the total score—had higher odds of dropping out at the initial milestones, but this effect diminished over time. This interaction relationship is illustrated in Figure 1, which plotted two prototypical groups that had misconception score scores ±1 standard deviation of the mean, while keeping all other covariates at their means (the variable new-chapter was kept at zero). According to post-GLM test ($\chi^2 = 0.94, p = .33$), the two groups were not statistically significantly different from each other starting from milestone 7, which was in the middle of the course chapter that discussed measuring the distance, mass and size of exoplanets.

The model also contained time-varying predictors related to participants' in-class performances, respectively, the score in the previous pset (pscore) and the time spent in the previous milestone session (active_time). We found both pscore and active_time to have significant main effects. This indicated that, regardless of which milestone students had progressed to, the lower their scores were the pset, and the less time they spent on the milestone, the higher were their odds of dropout in the following milestone.

In summary, this study had three main results. First, we discovered several predictors of dropout whose effects did not diminish over time (i.e., remained constant throughout the milestone sequence): location, age, intention to complete, English skills, prior familiarity to the

![FIGURE 1](https://example.com/figure1.png)

**FIGURE 1** Plotting the fitted probability of dropout by misconception score levels (mean ± 1 SD) with 95% confidence intervals [Color figure can be viewed at wileyonlinelibrary.com]
subject, and motivation to earn a certificate, score and time spent in the previous pset. Second, we did not find gender, education level, number of previous MOOCs completed, and motivation to participate in online forums to have significant effects on the likelihood of dropout after controlling for other variables. Third, our finding rejected the hypothesis that preexisting misconceptions have a positive motivating effect on course retention, and it supported the competing hypothesis that misconceptions predict dropout. Moreover, the effect of misconceptions was strong at the beginning, but diminished over the course of the milestone sequence.

4 | DISCUSSION

We first discuss the implications of our findings for MOOCs research and practice and then focus on their contribution to the misconception literature in traditional classroom settings.

The most important finding of this study was the effect of the misconception score, which had an interaction effect with milestones. This result confirmed a prior study (Chen et al., 2019) that has shown that prior acquaintance within the knowledge domain had a positive effect on persistence and that this effect decreased as students progressed through the milestones. The test for preexisting knowledge adopted by the prior study was an aptitude test to examine students’ algorithmic and logic skills before learning computer programming. The pretest in this study was the first test, to our knowledge, that measured students’ misconceptions in a MOOC study. Therefore, it provided the first evidence to show that misconceptions influence students’ dropout rates in MOOCs. Specifically, misconceptions pose an initial hurdle to participation. When the concepts covered by the course contradict the misconceptions held in students’ intuition, students might find the course content difficult to grasp early on.

The conceptual domains that were probed by the pretest (scale, energy, spectroscopy, and multi-factorial mental models) were fundamental to the understanding of the movement of spatial objects, the distance between the objects, the transfer of energy, and the observation of signals, which are the building blocks and reoccurring topics in the SPU30X. If misconceptions were not addressed in these domains, they would become troublesome knowledge that would block the learner not only from deep understanding but also from further inquiry. Here are a few examples:

1. a learner who assumes that the Sun produces energy by burning oxygen might expect that it would burn out over the course of a few thousand years;
2. a learner who assumes that our solar system was solely created by the Big Bang might find it ridiculous that Earth contains elements generated in supernovae;
3. a learner who holds an over-simplified notion of scale might underestimate the challenge presented by the vast distances in space exploration; and
4. a learner who holds misconceptions in spectroscopy, such as believing that all stars are white, could not make sense of how scientists make inferences about distant objects primarily based on observing the light from them.

We did not posit any particular misconceptions to trigger a learning obstacle at any particular course milestone, which is a challenge beyond the scope of this study. Our pretest sampled a limited number of misconceptions that learners may hold in their mental models. Our results did show that, controlling for the level of astronomy knowledge, holding larger numbers of misconceptions constitutes an additional obstacle to a learner’s persistence in the course,
suggesting that multiple encounters of a counterintuitive mismatch between the course contents and the learner’s existing conceptions exacerbate psychological burnout and the inclination to withdraw from further learning. As we discussed in the theoretical framework, the mismatch may activate three immediate reactions of the learners: cognitive conflict, disturbed expectation, plus frustration as a result of the two. This study did not explicitly measure any of the three possible reactions, but they may serve to explain the findings of the study from a theoretical perspective by positing a plausible mechanism.

The results also helped us decide between opposing predictions of the theories and thus update our understanding of these theories. If, according to cognitive conflict theory, cognitive conflict did occur, it was likely not motivating learners to resolve the conflict by persisting in the course, but it rather discouraged them from further inquiry, perhaps to avoid the discomfort or to ease the burnout of cognitive conflict. If, as implied by expectancy-value theory, preexisting misconceptions did lead to over-optimism about the learners’ existing knowledge, it appears that the over-optimism did not help them to persist as it was found in other STEM contexts, such as career interests (Bench et al., 2015), but that it rather frustrated the learners. Whereas this study could not determine which of the two theoretical frameworks was at work, it was able to conclude that holding distractive misconceptions was worse than lacking subject matter knowledge (recalling that we had controlled for the learners’ overall level of correctness in our model, those students who held neither the scientific knowledge nor a popular misconception were considered to have a lack of knowledge, or to hold idiosyncratic incomplete or erroneous beliefs—because few learners have a complete lack of knowledge) because the misconceptions would drive the learners astray and constitute an additional penalty to learners’ persistence, at least in the initially stages of a MOOC setting.

Interestingly, our study also showed that, as students kept participating in the course through the initial chapters, possibly by picking up increasing levels of content knowledge, resolving/inhibiting their misconceptions, adjusting their expectations and self-evaluations, and/or managing their frustrations, they would persist as well as those who had fewer misconceptions at the outset. We do not know if the learners had successfully resolved their misconceptions (as it has been proven very difficult to achieve), or if the resolved misconceptions were the reason that ameliorated the steep dropout trend. It is possible that learners may have gradually ignored their misconceptions (as misconception inhibition was found to be more common than misconception resolution), or managed their frustration, or adapted their estimation of the course difficulty and adjusted their learning effort (psychological cost) devoted to the course. Alternatively, our findings could be simply attributable to the possibility that those who felt the strongest discomfort about cognitive conflict or disturbed expectation had already dropped out in the initial stages, and those who stayed were not bothered by the discomfort. All these possible explanations call for more targeted studies in the future, as we will elaborate in the Limitation section.

Our findings lead to three major suggestions to astronomy MOOC instructors, or to MOOC instructors in general, if we assume generalizability beyond astronomy (see Section 5). First, MOOC instructors should make efforts to measure and understand students’ incoming knowledge, including misconceptions. It has been well documented that knowledge of students’ misconceptions (part of the PCK) is a crucial teaching skill for teachers to facilitate their students’ learning in traditional classrooms (Hill et al., 2005; Sadler et al., 2013); and such knowledge has proven to be useful in online settings as well (She & Liao, 2010; Wendt & Rockinson-Szapkiw, 2014). This study suggests that teachers should not only pay attention to how students’
misconceptions may affect their understanding and performance, but also how it may impede students from engaging in understanding and performing at all.

Second, MOOC instructors should actively address students’ misconceptions. Our original hypothesis that misconceptions may motivate learners to engage in more inquiry was based on the premise that learners have teachers or resources to turn to when their existing mental models were challenged. A common principle behind various cognitive-conflict-driven pedagogical approaches is that teachers should be aware of the students’ misconceptions so that they can purposefully use students’ cognitive dissonances as opportunities to either explicitly resolve the cognitive conflict (Bucat, 2015; Wartono & Putirulan, 2018), or promote the scientific explanation to surpass the misconception while they still coexist in the mind of the students (Potvin et al., 2015). Sadler et al. (2013) have shown that students cannot correct their misconceptions by themselves over time, and only students whose teachers have knowledge of student misconceptions can achieve conceptual change. In the absence of such facilitators, cognitive conflict may lead to frustration, and educational opportunities may be missed. One of the common and major shortcomings of the MOOC platform is the lack of customized attention and scaffolding. To address learners’ misconceptions individually may be costly for most MOOC platforms; however, considering the importance of misconceptions for students’ persistence, instructors should at least anticipate the most common misconceptions in the topic field and allocate time to address these misconceptions in the initial stages of the course.

Last, from an expectancy-value theory perspective, instructors should be aware that misconceptions may seriously bias students’ evaluation of self-competence and the expectation of success, as learners who hold strong misconceptions may assume they already have a working mental model or a good understanding of some of the content. Such an optimism is not sustainable once learners start the course and realize what they are learning is way more difficult and frustrating to grasp than they had expected. Instructors should help the learners set their expectation in the beginning of the course. For example, the instructors can review the pre-screening test with the learners, inform them about their misconceptions, and/or preview the expected learning curve of the course. Most importantly, the instructors should inform the learners that, as the learners persist in the course, they are expected to perceive smaller and smaller amounts of frustration induced by counterintuitive subject matter knowledge.

As noted in the Introduction, the general public, especially young learners, are naturally fascinated by astronomy or science in general, but this fascination often gives way to the mystification of science—believing that science is awe-inspiring, yet understandable only by a small group of geniuses (Dimopoulos & Koulaïdis, 2003; Evans, Krippendorf, Jae, Poslusnzy, & Thomas, 1990), settling on superficial knowledge and misconceptions, and preventing people from reconstructing their mental models to accommodate new knowledge. A lot of prior discussion in the misconception literature addressed how misconceptions make learning difficult. We argue that it is an even more troublesome and alarming problem in science education when misconceptions make learning stop completely in the very beginning stages. Our findings inspired us to ask a more philosophical question: is counter-intuitive knowledge hard to assimilate because it is difficult to resolve even if people take the time to attempt resolutions, or because people do not even take the time to wonder? This was precisely what Carl Frankenstein (1979) worried about 40 years ago—that cognitive conflict might increase learners’ frustration so much that they halt conflict resolution.

This philosophical speculation assumes an analogy between MOOC engagement and general science learning engagement, which is an open question. As pointed out in the introduction, dropping out from class or from school is always a costly decision in the traditional
educational system. In some situations, for example, if a class is elective, students can drop out within a few trial sessions, but the dropout rate is usually very low because of academic, financial, and peer pressures. Even though, as has been shown in prior studies, students may experience multiple moments of temporary defeat, or burnout, due to cognitive conflict or frustration (Khalaj & Savoji, 2018; Olwage & Mostert, 2014; Salanova et al., 2010), students rarely can afford to actually drop out. Therefore, the variation in attrition that might be explained by misconception is very small, which makes the traditional school setting impractical for studying the relationship between misconception and attrition. In the MOOCs setting, students can drop out at any time with very little cost, which is ideal for investigating factors influencing attrition. It is noteworthy that MOOCs are very different from traditional classes in many ways. For example, students were found to have higher satisfaction levels and higher learning outcomes in traditional classrooms than in an online environment (Smith, Wilson, Banks, Zhu, & Varma-Nelson, 2014). Wendt and Rockinson-Szapkiw (2014) further showed that online collaborative activities were less effective than in-classroom ones in addressing student misconceptions. Nevertheless, the construction of knowledge should follow similar progressions, and students should experience similar hurdles when they first encounter and acquire new concepts that are contrary to their prior beliefs. Based on the result of this study, we speculate that, in traditional classroom settings, students with prior misconceptions are prone to increased feelings of failure at the beginning of the class. This speculation appears to be difficult to test empirically in classrooms without extensive student observations, interviews, or surveys about their psychological states. However, we further predict, based on a weaker version of our speculation, that in an elective offline course that allows students to drop in a “trial period,” students who drop out in this period should have stronger prior and unresolved misconceptions, compared with students who persisted, controlling for equivalent scores in pre-tests. This prediction should be easy to test in future studies and would strengthen the analogy between MOOC engagement and classroom engagement. Earlier research (e.g., Brobst, Markworth, Tasker, & Ohana, 2017; Coe, Aloisi, Higgins, & Major, 2014; Sadler et al., 2013) has shown that teachers who understand students’ misconceptions tend to be high quality teachers and help students improve their grades in traditional classrooms. Part of this effect, as we further speculate, could be attributed to the phenomenon discussed in this article: as students’ misconceptions have been addressed, their frustration, thoughts of failure and intentions to give up, are eased. We suggest the reader be aware of the untested analogy between dropping out of a MOOC (and informal science learning activities) and the psychological resignation in the classroom. It is possible that our finding is only applicable to the MOOC settings (and perhaps the informal science learning domain). Future studies should investigate the interplay between teachers’ perceptions of students’ misconceptions, teachers’ pedagogies, and students’ misconceptions, frustration, resilience, and performance, in both online and offline classrooms.

5 | LIMITATIONS

Many of the above speculations about learners’ reasons to drop out could have been examined by simply asking the learners. Unfortunately, this study did not follow up with the learners at the end of the course. Had we contacted and interviewed the learners (especially those with strong misconceptions in the pretest) who persisted or dropped out, we would have an additional powerful source of data to make sense of their course participation decisions and their relationship with the misconceptions about astronomy in the learners’ mind.
A MOOC such as SPU30X, which teaches about the search for Earth-like planets and alien life, is fundamentally different from MOOCs that teach immediately useful skills or tools, such as computer programming or statistics. In comparison, SPU30X participants were more likely to be driven by personal interests—like hobbyists—rather than driven by occupational skill development. Compared, for instance, with the MOOC CS50x Introduction to Computer Science, the content in SPU30X contains more narratives, similar to educational documentaries, and is much less demanding of prior mathematic, logic, or language skills. The completion rate of SPU30X (23%) is above the average completion rates (15%, ranging between 5% and 40%) reported in the MOOC literature (Jordan, 2015). Thus, this study contributes to MOOC research by its coverage of a hobbyist MOOC, a type of MOOC less examined by researchers. Yet, for the same reason, caution should be taken when generalizing the results of this study to other types of MOOCs. Nevertheless, by successfully replicating the effects of many covariates that have been well documented by the studies of other MOOCs, it appears plausible that SPU30X was not overly different from the general MOOCs family after all.

Another limitation of the study was that we did not keep track of the misconceptions over the course, which limited our ability to examine the mechanism behind the association between misconceptions and retention. Had we directly measured learners’ misconceptions repeatedly over the milestones (such as including misconception measures in the psets, instead of using the actual psets that only revisited course content and had very low difficulty), we could inspect if the misconceptions were gradually resolved and if the change in misconceptions was associated with the change in dropout hazard. Lastly, we could not explicitly discuss what it means that the probability of dropout converged at around milestone 7 between the high and low misconception groups. Milestone 7 was in the middle of the second chapter that discussed the measurement of distance, mass and size. It may be strongly related to misconceptions in scale and spectroscopy that we measured in the pretest. However, we do not suggest there to be a precisely aligned relationship between the content in the chapter and the measured misconceptions for two reasons: First, scale and spectroscopy concepts were not only applied to chapter two. They have been introduced in the first chapter that discussed the position and environment of Earth that made life possible, and also repeatedly applied in later chapters about observing features of the exoplanets. Second, the misconceptions included in the presurvey served to collect a sample of learners' misconceptions and were not comprehensive enough to diagnose the exact domains of misconceptions the learners held. Thus, a higher misconception score should be interpreted as having more misconceptions about astronomy in general. In short, this study cannot detect the specific misconceptions that interacted with the course content at specific milestones, because we did not cover milestone-specific misconceptions in the pretest and only measured misconceptions that were widely applicable to most of the milestones.

6 | CONCLUSION

To our knowledge, this is the first study to show students’ misconceptions to be an obstacle to persistence in the initial sessions of a MOOC. We also found students’ performance and engagement in the most recent milestone to predict their persistence in the following milestone. These findings have very clear policy implications for improving the design and teaching of the next generation MOOCs.
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CONFLICT OF INTEREST
The authors have no conflict of interest to declare.

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REFERENCES
Abeer, W., & Miri, B. (2014). Students’ preferences and views about learning in a MOOC. *Procedia-Social and Behavioral Sciences*, 152, 318–323.

Abraham, J. K., Perez, K. E., Downey, N., Herron, J. C., & Meir, E. (2012). Short lesson plan associated with increased acceptance of evolutionary theory and potential change in three alternate conceptions of macro-evolution in undergraduate students. *CBE—Life Sciences Education*, 11(2), 152–164.

Alfieri, L., Nokes-Malach, T. J., & Schunn, C. D. (2013). Learning through case comparisons: A meta-analytic review. *Educational Psychologist*, 48(2), 87–113.

Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education*, 80, 28–38.

Anderson, A., Huttenlocher, D., Kleinberg, J., & Leskovec, J. (2014). Engaging with massive online courses. In *WWW’14 Proceedings of the 23rd international conference on World Wide Web* (pp. 687–698).

Appleton, K. (2008). Developing science pedagogical content knowledge through mentoring elementary teachers. *Journal of Science Teacher Education*, 19(6), 523–545.

Ashmann, S. (2012). A sun-earth-moon activity to develop student understanding of lunar phases and frames of reference. *Science Scope*, 35(6), 32–36.

Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. *Psychological Review*, 64(6p1), 359–372.

Bailey, J. M., & Slater, T. F. (2003). A review of astronomy education research. *Astronomy Education Review*, 2(2), 20–45.

Baker, R., Evans, B., & Dee, T. (2016). A randomized experiment testing the efficacy of a scheduling nudge in a massive open online course (MOOC). *AERA Open*, 2(4), 2332858416674007.

Baker, R., Evans, B., Greenberg, E., & Dee, T. (2014). Understanding persistence in MOOCs (Massive Open Online Courses): Descriptive & experimental evidence. Paper presented at the European MOOC stakeholder Summit 2014, Lausanne, Switzerland.

Ball, D. L., & Bass, H. (2000). Interweaving content and pedagogy in teaching and learning to teach: Knowing and using mathematics. In J. Boaler (Ed.), *Multiple perspectives on the teaching and learning of mathematics* (pp. 83–104). Westport, CT: Ablex.

Bao, L., & Redish, E. F. (2006). Model analysis: Representing and assessing the dynamics of student learning. *Physical Review Special Topics-Physics Education Research*, 2(1), 010103.

Barak, M., Watted, A., & Haick, H. (2016). Motivation to learn in massive open online courses: Examining aspects of language and social engagement. *Computers & Education*, 94, 49–60.

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn? A taxonomy for far transfer. *Psychological Bulletin*, 128(4), 612–637.

Barrier, R. M. (2010). Astronomical misconceptions. *The Physics Teacher*, 48(5), 319–321.
Bask, M., & Salmela-Aro, K. (2013). Burned out to drop out: Exploring the relationship between school burnout and school dropout. *European Journal of Psychology of Education, 28*(2), 511–528.

Baumert, J., Kunter, M., Blum, W., Brunner, M., Voss, T., Jordan, A., ... Tsai, Y. M. (2010). Teachers' mathematical knowledge, cognitive activation in the classroom, and student progress. *American Educational Research Journal, 47*(1), 133–180.

Belanger, Y., & Thornton, J. (2013). *Bioelectricity: A quantitative approach Duke University's first MOOC*. Retrieved from http://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/6216/Duke_Bioelectricity_MOOC_Fall2012.pdf?sequence=141.

Bell, F. (2011). Connectivism: Its place in theory-informed research and innovation in technology-enabled learning. *The International Review of Research in Open and Distributed Learning, 12*(3), 98–118.

Bench, S. W., Lench, H. C., Miner, K., Flores, S. A., & Liew, J. (2015). Gender gaps in overestimation of math performance. *Sex Roles, 72*, 536–546.

Bergstrom, Z., Sadler, P., & Sonnert, G. (2016). Evolution and persistence of students' astronomy career interests: A gender study. *Journal of Astronomy & Earth Sciences Education, 3*(1), 77–92.

Bryce, T. G. K., & MacMillan, K. (2009). Momentum and kinetic energy: Confusable concepts in secondary school physics. *Journal of Research in Science Teaching, 46*(7), 739–761.

Bucat, R. B. (2015). Using the cognitive conflict strategy with classroom chemistry demonstrations. *Chemistry Education: Best Practices, Opportunities and Trends* (pp. 447–468). Weinheim, Germany: Wiley-VCH Verlag GmbH & Co. KGaA.

Cavagnetto, A. R., & Kurtz, K. J. (2016). Promoting students' attention to argumentative reasoning patterns. *Science Education, 100*(4), 625–644.

Champagne, A. B., Gunstone, R. F., & Klopfer, L. E. (1985) Effecting changes in cognitive structures among physics students. In L. West & A. Pines (Eds.), *Cognitive Structure and Conceptual Change*, Academic Press, Orlando, FL, 163–188.

Chen, C., Schneps, M. H., & Sonnert, G. (2016). Order matters: Sequencing scale-realistic versus simplified models to improve science learning. *Journal of Science Education and Technology, 25*(5), 806–823.

Chen, C., Sonnert, G., & Sader, P. M. (2019). Factors predicting retention in computer science MOOC: A survival analysis of pre-computational thinking and auto-feedback. American Educational Research Association Annual Meeting, Toronto. DOI: 10.302/1443355.

Chen, Y. L., Pan, P. R., Sung, Y. T., & Chang, K. E. (2013). Correcting misconceptions on electronics: Effects of a conceptual change model. *Journal of Educational Technology & Society, 16*(2), 212–227.

Chen, Z., Chudzicki, C., Palumbo, D., Alexandron, G., Choi, Y. J., Zhou, Q., & Pritchard, D. E. (2016). Researching for better instructional methods using AB experiments in MOOCs: Results and challenges. *Research and Practice in Technology Enhanced Learning, 11*(1), 9.

Chi, M. T. (1992). Conceptual change within and across ontological categories: Implications for learning and discovery in sciences. In R. Giere (Ed.), *Cognitive models of science: Minnesota studies in the philosophy of science* (pp. 129–186). Minneapolis: University of Minnesota Press.

Chi, M. T. (2005). Commonsense conceptions of emergent processes: Why some misconceptions are robust. *The Journal of the Learning Sciences, 14*(2), 161–199.

Chi, M. T., Slotta, J. D., & De Leeuw, N. (1994). From things to processes: A theory of conceptual change for learning science concepts. *Learning and Instruction, 4*(1), 27–43.

Chiu, M. H., Chou, C. C., & Liu, C. J. (2002). Dynamic processes of conceptual change: Analysis of constructing mental models of chemical equilibrium. *Journal of Research in Science Teaching, 39*(8), 688–712.

Chow, T. C., & Treagust, D. (2013). An intervention study using cognitive conflict to foster conceptual change. *Journal of Science and Mathematics Education in Southeast Asia, 36*(1), 44–64.
Chudzicki, C. A. (2015). *Learning experiments in a MOOC (massive open online course)* (Doctoral dissertation, Massachusetts institute of technology).

Clark, D. B. (2006). Longitudinal conceptual change in students’ understanding of thermal equilibrium: An examination of the process of conceptual restructuring. *Cognition and Instruction, 24*(4), 467–563.

Coe, R., Aloisi, C., Higgins, S., & Major, L. E. (2014). *What makes great teaching? Review of the underpinning research. Project report.* London: Sutton Trust.

Coffrin, C., Corrin, L., de Barba, P., & Kennedy, G. (2014). Visualizing patterns of student engagement and performance in MOOCs. In *Proceedings of the fourth international conference on learning analytics and knowledge* (pp. 83–92). ACM.

Colvin, K. F., Champaign, J., Liu, A., Zhou, Q., Fredericks, C., & Pritchard, D. E. (2014). Learning in an introductory physics MOOC: All cohorts learn equally, including an on-campus class. *The International Review of Research in Open and Distributed Learning, 15*(4), 263–283.

Comins, N. F. (1998). Identifying and addressing astronomy misconceptions in the classroom. In L. Gouguenheim, D. McNally & ve J.R. Percy, *New trends in astronomy teaching.* (pp. 118–123). Cambridge, UK: Cambridge University Press.

De Barba, P. G., Kennedy, G. E., & Ainley, M. D. (2016). The role of students’ motivation and participation in predicting performance in a MOOC. *Journal of Computer Assisted Learning, 32*(3), 218–231.

De Dreu, C. K., & Weingart, L. R. (2003). Task versus relationship conflict, team performance, and team member satisfaction: A meta-analysis. *Journal of Applied Psychology, 88*(4), 741–749.

De Posada, J. M. (1997). Conceptions of high school students concerning the internal structure of metals and their electric conduction: Structure and evolution. *Science Education, 81*(4), 445–467.

De Waard, I., Koutropoulos, A., Keskin, N., Abajian, S. C., Hogue, R., Rodriguez, C. O., & Gallagher, M. S. (2011). Exploring the MOOC format as a pedagogical approach for mLearning. In *Proceedings of 10th World Conference on Mobile and Contextual Learning* (pp. 138–145).

DeBoer, G. E., Quellmalz, E. S., Davenport, J. L., Timms, M. J., Herrmann-Abell, C. F., Buckley, B. C.,... Flanagan, J. C. (2014). Comparing three online testing modalities: Using static, active, and interactive online testing modalities to assess middle school students’ understanding of fundamental ideas and use of inquiry skills related to ecosystems. *Journal of Research in Science Teaching, 51*(4), 523–554.

Dega, B. G., Kriek, J., & Mogese, T. F. (2013). Students' conceptual change in electricity and magnetism using simulations: A comparison of cognitive perturbation and cognitive conflict. *Journal of Research in Science Teaching, 50*(6), 677–698.

Delgado, C., & Lucero, M. M. (2015). Scale construction for graphing: An investigation of students’ resources. *Journal of Research in Science Teaching, 52*(5), 633–658.

Dillahunty, T. R., Wang, B. Z., & Teasley, S. (2014). Democratizing higher education: Exploring MOOC use among those who cannot afford a formal education. *The International Review of Research in Open and Distributed Learning, 15*(5), 177–195.

Dimopoulos, K., & Koulaidis, V. (2003). Science and technology education for citizenship: The potential role of the press. *Science Education, 87*(2), 241–256.

DiSessa, A. A. (1993). Toward an epistemology of physics. *Cognition and Instruction, 10*(2–3), 105–225.

Duque, L. C. (2014). A framework for analysing higher education performance: Students' satisfaction, perceived learning outcomes, and dropout intentions. *Total Quality Management & Business Excellence, 25*(1–2), 1–21.

Durksen, T. L., Chu, M. W., Ahmad, Z. F., Radil, A. I., & Daniels, L. M. (2016). Motivation in a MOOC: A probabilistic analysis of online learners’ basic psychological needs. *Social Psychology of Education, 19*(2), 241–260.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents’ achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215–225.

Eckstein, S. G., & Shemesh, M. (1993). Stage theory of the development of alternative conceptions. *Journal of Research in Science Teaching, 30*(1), 45–64.

Ensminger, M. E., & Slusarcick, A. L. (1992). Paths to high school graduation or dropout: A longitudinal study of a first-grade cohort. *Sociology of Education, 65*(2), 95–113.

Ergönenç, J., Neumann, K., & Fischer, H. E. (2014). The impact of pedagogical content knowledge on cognitive activation and student learning. In H. E. Fischer, P. Labudde, K. Neumann, & J. Viiri (Eds.), *Quality of instruction in physics* (pp. 145–160). Münster: Waxmann.
Eryilmaz, A. (2002). Effects of conceptual assignments and conceptual change discussions on students’ misconceptions and achievement regarding force and motion. Journal of Research in Science Teaching, 39, 1001–1015.

Evans, W. A., Krippendorf, M., Jae, H. Y., Posluszny, P., & Thomas, S. (1990). Science in the prestige and national tabloid presses. Social Science Quarterly, 71(1), 105.

Fan, W., & Wolters, C. A. (2014). School motivation and high school dropout: The mediating role of educational expectation. British Journal of Educational Psychology, 84(1), 22–39.

Fanetti, T. M. (2001). The relationships of scale concepts on college age students’ misconceptions about the cause of the lunar phases. Iowa State University: Master’s thesis.

Festinger, L. (1957). A theory of cognitive dissonance. Stanford, CA: Stanford University Press.

Fisher, K. M. (1985). A misconception in biology: Amino acids and translation. Journal of Research in Science Teaching, 22(1), 53–62.

Foisy, L. M. B., Potvin, P., Riopel, M., & Masson, S. (2015). Is inhibition involved in overcoming a common physics misconception in mechanics? Trends in Neuroscience and Education, 4(1–2), 26–36.

Frankenstein, C. (1979). They think again. New York: Van Nostrand.

Gadgil, S., Nokes-Malach, T. J., & Chi, M. T. (2012). Effectiveness of holistic mental model confrontation in driving conceptual change. Learning and Instruction, 22(1), 47–61.

Gan, Y., Shang, J., & Zhang, Y. (2007). Coping flexibility and locus of control as predictors of burnout among Chinese college students. Social Behavior and Personality: An International Journal, 35(8), 1087–1098.

Gasevic, D., Kovanovic, V., Joksimovic, S., & Siemens, G. (2014). Where is research on massive open online courses headed? A data analysis of the MOOC research initiative. The International Review of Research in Open and Distributed Learning, 15(5), 1–29.

Gelman, S. A. (2011). When worlds collide–or do they? Implications of explanatory coexistence for conceptual development and change. Human Development, 54(3), 185–190.

Gentner, D., & Wolff, P. (2000). Metaphor and knowledge change. In E. Dietrich & A. Markman (Eds.), Cognitive Dynamics: Conceptual Change in Humans and Machines. Cambridge, MA: MIT Press.

Gilbert, J. K. (2004). Models and modelling: Routes to more authentic science education. International Journal of Science and Mathematics Education, 2(2), 115–130.

Goldwater, M. B., & Schalk, L. (2016). Relational categories as a bridge between cognitive and educational research. Psychological Bulletin, 142(7), 729–757.

Gormally, C., Brickman, P., & Lutz, M. (2012). Developing a test of scientific literacy skills (TOSLS): Measuring undergraduates’ evaluation of scientific information and arguments. CBE—Life Sciences Education, 11(4), 364–377.

Gould, R., Dussault, M., & Sadler, P. (2006). What’s educational about online telescopes? Evaluating 10 years of MicroObservatory. Astronomy Education Review, 5(2), 127–145.

Gould, R., Sunbury, S., & Dussault, M. (2014). In praise of messy data. The Science Teacher, 81(8), 31.

Gould, R., Sunbury, S., & Krumhansl, R. (2012). Using online telescopes to explore exoplanets from the physics classroom. American Journal of Physics, 80(5), 445–451.

Greene, J. A., Oswald, C. A., & Pomerantz, J. (2015). Predictors of retention and achievement in a massive open online course. American Educational Research Journal, 52(5), 925–955.

Grossman, P. L. (1990). The making of a teacher: Teacher knowledge and teacher education. New York: Teachers College Press.

Grünewald, F., Meinel, C., Totschnig, M., & Willems, C. (2013). Designing MOOCs for the support of multiple learning styles. In European conference on technology enhanced learning (pp. 371–382). Berlin, Heidelberg: Springer.

Guzzetti, B. J. (2000). Learning counter-intuitive science concepts: What have we learned from over a decade of research? Reading & Writing Quarterly, 16(2), 89–98.

Ha, M. S., Lee, J. K., & Cha, H. Y. (2006). A cross-sectional study of students’ conceptions on evolution and characteristics of concept formation about it in terms of the subjects: Human, animals and plants. Journal of the Korean Association for Science Education, 26(7), 813–825.

Haggard, S. (2013). The maturing of the MOOC. Department for Business Innovation & Skills. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/240193/13-1173-maturing-of-the-mooc.pdf
Halawa, S., Greene, D., & Mitchell, J. (2014). Dropout prediction in MOOCs using learner activity features. Proceedings of the 2nd European MOOCs Stakeholders Summit (pp. 58–65).

Halim, L., & Meerah, S. M. M. (2002). Science trainee teachers’ pedagogical content knowledge and its influence on physics teaching. Research in Science & Technological Education, 20(2), 215–225.

Harmon-Jones, E., Amodio, D. M., & Harmon-Jones, C. (2009). Action-based model of dissonance: A review, integration, and expansion of conceptions of cognitive conflict. Advances in Experimental Social Psychology, 41, 119–166.

Hartnett, M., George, A. S., & Dron, J. (2014). Exploring motivation in an online context: A case study. Contemporary Issues in Technology and Teacher Education, 14(1), 31–53.

He, J., Bailey, J., Rubinstein, B. I., & Zhang, R. (2015). Identifying at-risk students in massive open online courses. In AAAI (pp. 1749–1755).

Heddy, B. C., & Sinatra, G. M. (2013). Transforming misconceptions: Using transformative experience to promote positive affect and conceptual change in students learning about biological evolution. Science Education, 97(5), 723–744.

Heller, J. I., Daehler, K. R., Wong, N., Shinohara, M., & Miratrix, L. W. (2012). Differential effects of three professional development models on teacher knowledge and student achievement in elementary science. Journal of Research in Science Teaching, 49(3), 333–362.

Hewson, P. W., & Hewson, M. G. (1984). The role of conceptual conflict in conceptual change and the design of science instruction. Instructional Science, 13, 1–13.

Hewson, P. W., & Thorley, N. R. (1989). The conditions of conceptual change in the classroom. International Journal of Science Education, 11(5), 541–553.

Hill, H. C., Rowan, B., & Ball, D. L. (2005). Effects of teachers' mathematical knowledge for teaching on student achievement. American Educational Research Journal, 42(2), 371–406.

Hill, P. (2013). Emerging student patterns in MOOCs: A (revised) graphical view. http://mfeldstein.Com/Emerging-Student-Patterns-in-Moocs-a-Revised-Graphical-View.

Holder, B. (2007). An investigation of hope, academics, environment, and motivation as predictors of persistence in higher education online programs. The Internet and Higher Education, 10(4), 245–260.

Hollands, F. M., & Tirthali, D. (2014). MOOCs: Expectations and reality. Full report. Online Submission.

Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. Computers & Education, 98, 157–168.

Ioannides, C., & Vosniadou, S. (2002). The changing meanings of force. Cognitive Science Quarterly, 2(1), 5–62.

Ivanjek, L., Shaffer, P. S., McDermott, L. C., Planinic, M., & Veza, D. (2015). Research as a guide for curriculum development: An example from introductory spectroscopy. I. Identifying student difficulties with atomic emission spectra. American Journal of Physics, 83(1), 85–90.

Jacobs, A. J. (2013). Two cheers for web U. New York Times, 162(56113), 1–7.

Jiang, S., Williams, A., Schenke, K., Warschauer, M., & O’dowd, D. (2014). Predicting MOOC performance with week 1 behavior. In Educational Data Mining 2014.

Jordan, K. (2015). MOOC completion rates, 2015. http://www.katyjordan.com/MOOCproject.html, 4.

Joyner, D. A. (2017). Congruency, adaptivity, modularity, and personalization: Four experiments in teaching introduction to computing. In Proceedings of the Fourth (2017) ACM Conference on Learning@ Scale (pp. 307–310). ACM.

Kang, H., Scharmann, L. C., Kang, S., & Noh, T. (2010). Cognitive conflict and situational interest as factors influencing conceptual change. International Journal of Environmental and Science Education, 5(4), 383–405.

Keller, M. M., Neumann, K., & Fischer, H. E. (2017). The impact of physics teachers' pedagogical content knowledge and motivation on students’ achievement and interest. Journal of Research in Science Teaching, 54(5), 586–614.

Kellermanns, F. W., & Floyd, S. W. (2005). Strategic consensus and constructive confrontation: Unifying forces in the resource accumulation process. In S. W. Floyd, J. Ross, C. Jacobs, & F. W. Kellermanns (Eds.), Innovating strategy process (pp. 149–162). Oxford: Blackwell.

Kellogg, S. (2013). Online learning: How to make a MOOC. Nature, 499(7458), 369–371.

Kennedy, D. (2005). Anniversary reflections. Science, 309(5738), 1153–1153.
Kennedy, G., Coffrin, C., De Barba, P., & Corrin, L. (2015). Predicting success: How learners’ prior knowledge, skills and activities predict MOOC performance. In Proceedings of the fifth international conference on learning analytics and knowledge (pp. 136–140). ACM.

Khalaj, E., & Savoji, A. P. (2018). The effectiveness of cognitive self-regulatory education on academic burnout and cognitive dissonance and academic achievement of elementary students. Middle East Journal of Family Medicine, 7(10), 225.

Khalil, H., & Ebner, M. (2014). MOOCs completion rates and possible methods to improve retention—a literature review. In EdMedia+ Innovate Learning (pp. 1305–1313). Association for the Advancement of Computing in Education (AACE).

Kizilcec, R. F., & Halawa, S. (2015). Attrition and achievement gaps in online learning. In Proceedings of the Second (2015) ACM Conference on Learning@ Scale (pp. 57–66). ACM.

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. In Proceedings of the third international conference on learning analytics and knowledge (pp. 170–179). ACM.

Kloft, M., Stiehler, F., Zheng, Z., & Pinkwart, N. (2014). Predicting MOOC dropout over weeks using machine learning methods. In Proceedings of the EMNLP 2014 Workshop on Analysis of Large Scale Social Interaction in MOOCs (pp. 60–65).

Krstovic, M., Brown, L., Chacko, M., & Trinh, B. (2008). Grade 9 astronomy study: Interests of boys and girls studying astronomy at Fletcher’s meadow secondary school. Astronomy Education Review, 7(2), 18–24.

Kurtz, K. J., Boukrina, O., & Gentner, D. (2013). Comparison promotes learning and transfer of relational categories. Journal of Psychological Learning, Memory, and Cognition, 39(4), 1303.

Labobar, H., Setyosari, P., Degeng, I. N. S., & Dasna, I. W. (2015). The effect of cognitive conflict strategy to chemical conceptual change. International Journal of Science and Research (IJSR), 6(4), 2350–2352.

Larkin, D. (2012). Misconceptions about “misconceptions”: Preservice secondary science teachers’ views on the value and role of student ideas. Science Education, 96, 927–959.

Lawson, A. E. (1988). The acquisition of biological knowledge during childhood: Cognitive conflict or tabula rasa? Journal of Research in Science Teaching, 25(3), 185–199.

Lawson, A. E., & Weser, J. (1990). The rejection of nonscientific beliefs about life: Effects of instruction and reasoning skills. Journal of Research in Science Teaching, 27(6), 589–606.

Lee, G., & Byun, T. (2012). An explanation for the difficulty of leading conceptual change using a counterintuitive demonstration: The relationship between cognitive conflict and responses. Research in Science Education, 42(5), 943–965.

Lee, G., Kwon, J., Park, S.-S., Kim, J.-W., Kwon, H.-G., & Park, H.-K. (2003). Development of an instrument for measuring cognitive conflict in secondary-level science class. Journal of Research in Science Teaching, 40(6), 585–603.

Lee, H. S., Linn, M. C., Varma, K., & Liu, O. L. (2010). How do technology-enhanced inquiry science units impact classroom learning? Journal of Research in Science Teaching, 47(1), 71–90.

Legare, C. H., & Visala, A. (2011). Between religion and science: Integrating psychological and philosophical accounts of explanatory coexistence. Human Development, 54(3), 169–184.

Leonard, M. J., Kalinowski, S. T., & Andrews, T. C. (2014). Misconceptions yesterday, today, and tomorrow. CBE—Life Sciences Education, 13(2), 179–186.

Li, S. C., Law, N., & Lui, K. F. A. (2006). Cognitive perturbation through dynamic modelling: A pedagogical approach to conceptual change in science. Journal of Computer Assisted Learning, 22(6), 405–422.

Liu, O. L., Lee, H. S., & Linn, M. C. (2011). Measuring knowledge integration: Validation of four-year assessments. Journal of Research in Science Teaching, 48(9), 1079–1107.

Luscombe, J., Lewis, I., & Biggs, H. C. (2013). Essential elements for recruitment and retention: Generation Y. Education and Training, 55(3), 272–290.

Mackness, J., Waite, M., Roberts, G., & Lovegrove, E. (2013). Learning in a small, task-oriented, connectivist MOOC: Pedagogical issues and implications for higher education. The International Review of Research in Open and Distributed Learning, 14(4), 140–159.

Magen-Nagar, N., & Cohen, L. (2017). Learning strategies as a mediator for motivation and a sense of achievement among students who study in MOOCs. Education and Information Technologies, 22(3), 1271–1290.
Magneunsson, S., Krajcik, J., & Borko, H. (1999). Nature, sources, and development of pedagogical content knowledge for science teaching. In *Examining pedagogical content knowledge* (pp. 95–132). Dordrecht: Springer.

Maslach, C., Jackson, S. E., Leiter, M. P., Schaufeli, W. B., & Schwab, R. L. (1986). *Maslach burnout inventory* (Vol. 21, pp. 3463–3464). Palo Alto, CA: Consulting Psychologists Press.

Masson, S., Potvin, P., Riopel, M., & Foisy, L. M. B. (2014). Differences in brain activation between novices and experts in science during a task involving a common misconception in electricity. *Mind, Brain, and Education*, 8(1), 44–55.

Matlen, B. J., & Klahr, D. (2013). Sequential effects of high and low instructional guidance on children’s acquisition of experimentation skills: Is it all in the timing? *Instructional Science*, 41(3), 621–634.

Meek, S. E., Blakemore, L., & Marks, L. (2017). Is peer review an appropriate form of assessment in a MOOC? Student participation and performance in formative peer review. *Assessment & Evaluation in Higher Education*, 42(6), 1000–1013.

Meirchy, Y. J. (1993). The impact of science curricula on student views about the nature of science. *Journal of Research in Science Teaching*, 30(5), 429–443.

Merton, R. K. (1987). Three fragments from a sociologist’s notebooks: Establishing the phenomenon, specified ignorance, and strategic research materials. *Annual Review of Sociology*, 13(1), 1–29.

Meyer, J. H., & Land, R. (2006). Threshold concepts and troublesome knowledge: An introduction. In *Overcoming barriers to student understanding* (pp. 27–42). Routledge.

Miller, B. W., & Brewer, W. F. (2010). Misconceptions of astronomical distances. *International Journal of Science Education*, 32(12), 1549–1560.

Milligan, C., Littlejohn, A., & Margaryan, A. (2013). Patterns of engagement in connectivist MOOCs. *MERLOT Journal of Online Learning and Teaching*, 9(2), 149–159.

Mooney, A. C., Holahan, P. J., & Amason, A. C. (2007). Don’t take it personally: Exploring cognitive conflict as a mediator of affective conflict. *Journal of Management Studies*, 44(5), 733–758.

Mortagy, Y., Boghikian-Whitby, S., & Helou, I. (2018). An analytical investigation of the characteristics of the dropout students in higher education. *Issues in Informing Science and Information Technology*, 15, 249–278.

National Research Council. (1996). *National Science Education Standards*. Washington: National Academy Press.

Nawrot, I., & Doucet, A. (2014). Building engagement for MOOC students: Introducing support for time management on online learning platforms. In *Proceedings of the 23rd International Conference on world wide web* (pp. 1077–1082). ACM.

Nehm, R. H., Beggrow, E. P., Opfer, J. E., & Ha, M. (2012). Reasoning about natural selection: Diagnosing contextual competency using the ACORNS instrument. *The American Biology Teacher*, 74(2), 92–98.

Nixon, R. S., Campbell, B. K., & Luft, J. A. (2016). Effects of subject-area degree and classroom experience on new chemistry teachers’ subject matter knowledge. *International Journal of Science Education*, 38(10), 1636–1654.

Núñez, M. M., Gené, O. B., & Blanco, Á. F. (2014). Social community in MOOCs: Practical implications and outcomes. In *Proceedings of the Second International Conference on Technological Ecosystems for Enhancing Multiculturality* (pp. 147–154). ACM.

Oliver, M. (2011). Teaching and learning evolution: Testing the principles of a constructivist approach through action research. *Teaching Science: The Journal of the Australian Science Teachers Association*, 57(1), 13–18.

Olwage, D., & Mostert, K. (2014). Predictors of student burnout and engagement among university students. *Journal of Psychology in Africa*, 3(4), 346–350.

Özdemir, G., & Clark, D. B. (2007). An overview of conceptual change theories. *Eurasia Journal of Mathematics, Science & Technology Education*, 3(4), 351–361.

Peng, D., & Aggarwal, G. (2015) *Modeling MOOC Dropouts*. Retrieved from http://cs229.stanford.edu/proj2015/235_report.pdf

Perkins, D. (1999). The many faces of constructivism. *Educational Leadership*, 57(3), 6–11.

Perkins, D. (2006). Constructivism and troublesome knowledge. In *Overcoming barriers to student understanding* (pp. 57–71). Routledge.

Peterson, P. L., Carpenter, T., & Fennema, E. (1989). Teachers’ knowledge of students’ knowledge in mathematics problem solving: Correlational and case analyses. *Journal of Educational Psychology*, 81(4), 558–569.

Piaget, J. (1967). The mental development of the child. In D. Elkind (Ed.), *Six psychological studies*. New York: Random House.
Pintrich, P. R., Marx, R. W., & Boyle, R. A. (1993). Beyond cold conceptual change: The role of motivational beliefs and classroom contextual factors in the process of conceptual change. *Review of Educational Research, 63*(2), 167–199.

Plummer, J. D. (2006). *Students’ development of astronomy concepts across time* (PhD dissertation, University of Michigan, AAT 3238058).

Plummer, J. D., & Krajek, J. (2010). Building a learning progression for celestial motion: Elementary levels from an earth-based perspective. *Journal of Research in Science Teaching, 47*(7), 768–787.

Plummer, J. D., & Maynard, L. (2014). Building a learning progression for celestial motion: An exploration of students’ reasoning about the seasons. *Journal of Research in Science Teaching, 51*(7), 902–929.

Pope, J. (2014). *What are MOOCs good for?* Retrieved from the MIT Technology Review Web site: http://www.technologyreview.com/review/533406/what-are-moocs-good-for/

Posner, G. J., Strike, K. A., Hewson, P. W., & Gertzog, W. A. (1982). Accommodation of a scientific conception: Toward a theory of conceptual change. *Science Education, 66*(2), 211–227.

Potvin, P., & Cyr, G. (2017). Toward a durable prevalence of scientific conceptions: Tracking the effects of two interfering misconceptions about buoyancy from preschoolers to science teachers. *Journal of Research in Science Teaching, 54*(9), 1121–1142.

Potvin, P., Sauriol, É., & Riopel, M. (2015). Experimental evidence of the superiority of the prevalence model of conceptual change over the classical models and repetition. *Journal of Research in Science Teaching, 52*(8), 1082–1108.

Prather, E. E., Slater, T. F., & Offerdahl, E. G. (2002). Hints of a fundamental misconception in cosmology. *Astronomy Education Review, 1*(2), 28–34.

Prince, M. J., Vigeant, M. A., & Nottis, K. (2009). A preliminary study on the effectiveness of inquiry-based activities for addressing misconceptions of undergraduate engineering students. *Education for Chemical Engineers, 4*(2), 29–41.

Project 2061. (2001). *Atlas of scientific literacy*. Washington: American Association for the Advancement of Science.

Pursel, B. K., Zhang, L., Jablokow, K. W., Choi, G. W., & Velegol, D. (2016). Understanding MOOC students: Motivations and behaviours indicative of MOOC completion. *Journal of Computer Assisted Learning, 32*(3), 202–217.

Ramsburg, J. T., & Ohlsson, S. (2016). Category change in the absence of cognitive conflict. *Journal of Educational Psychology, 108*(1), 98–113.

Regan, A., Childs, P., & Hayes, S. (2011). The use of an intervention programme to improve under graduate students’ chemical knowledge and address their misconceptions. *Chemistry Education Research and Practice, 12*(2), 219–227.

Reich, J. (2014). *MOOC completion and retention in the context of student intent*. EDUCAUSE review online. http://www.educause.edu/ero/article/mooc-completion-and-retention-context-student-intent.

Rice, J. (2013). What I learned in MOOC. *College Composition and Communication, 64*(4), 695–703.

Riga, F., Winterbottom, M., Harris, E., & Newby, L. (2017). Inquiry-based science education. In K. S. Taber & B. Akpan (Eds.), *Science education: An international course companion* (pp. 247–261). Rotterdam, The Netherlands: Sense Publishers.

Rijndijk, C. (2000). Using astronomy as a vehicle for science education. *Publications of the Astronomical Society of Australia, 17*(2), 156–161.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78.

Sabella, M. S., & Redish, E. F. (2007). Knowledge organization and activation in physics problem solving. *American Journal of Physics, 75*(11), 1017–1029.

Sadler, P. (1996). Astronomy’s conceptual hierarchy. In J. Percy (Ed.), *Astronomy education: Current developments, future coordination* (pp. 26–34). CA: Astronomical Society of the Pacific. San Francisco.

Sadler, P. M. (1992). *The initial knowledge state of high school astronomy students*. (D.Ed. thesis), Graduate School of Education, Harvard University.

Sadler, P. M., Coyle, H., Miller, J. L., Cook-Smith, N., Dussault, M., & Gould, R. R. (2010). The astronomy and space science concept inventory: Development and validation of assessment instruments aligned with the K-12 national science standards. *Astronomy Education Review, 8*(1), 010111.
Sadler, P. M., Sonnert, G., Coyle-Smith, N., & Miller, J. L. (2013). The influence of teachers’ knowledge on student learning in middle school physical science classrooms. *American Educational Research Journal, 50*(5), 1020–1049.

Sadler, P. M., Sonnert, G., Hazari, Z., & Tai, R. (2012). Stability and volatility of STEM career interest in high school: A gender study. *Science Education, 96*(3), 411–427.

Salanova, M., Schaufeli, W., Martinez, L., & Bresó, E. (2010). How obstacles and facilitators predict academic performance: The mediating role of study burnout and engagement. *Anxiety, Stress & Coping, 23*(1), 53–70.

Sawtelle, V., Brewe, E., & Kramer, L. H. (2012). Exploring the relationship between self-efficacy and retention in introductory physics. *Journal of Research in Science Teaching, 49*(9), 1096–1121.

Schneider, M., & Hardy, I. (2013). Profiles of inconsistent knowledge in children's pathways of conceptual change. *Developmental Psychology, 49*(9), 1639–1649.

Shapiro, H. B., Lee, C. H., Roth, N. E. W., Li, K., Çetinkaya-Rundel, M., & Canelas, D. A. (2017). Understanding the massive open online course (MOOC) student experience: An examination of attitudes, motivations, and barriers. *Computers & Education, 110*, 35–50.

She, H. C. (2004). Fostering radical conceptual change through dual-situated learning model. *Journal of Research in Science Teaching: The Official Journal of the National Association for Research in Science Teaching, 41*(2), 142–164.

She, H. C., & Liao, Y. W. (2010). Bridging scientific reasoning and conceptual change through adaptive web-based learning. *Journal of Research in Science Teaching, 47*(1), 91–119.

Shtulman, A., & Lombrozo, T. (2016). Bundles of contradiction: A coexistence view of conceptual change. In D. Barner & A. S. Baron (Eds.), Core knowledge and conceptual change (pp. 53–72). Oxford: Oxford University Press.

Shtulman, A., Neal, C., & Lindquist, G. (2016). Children's ability to learn evolutionary explanations for biological adaptation. *Early Education and Development, 27*(8), 1222–1236.

Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. *Educational Researcher, 15*(2), 4–14.

Simons, T. L., & Peterson, R. S. (2000). Task conflict and relationship conflict in top management teams: The pivotal role of intragroup trust. *Journal of Applied Psychology, 85*(1), 102–111.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence.* New York: Oxford University Press.

Singh, C. (2007). Effect of misconception on transfer in problem solving. *AIP Conference Proceedings, 951*(1), 196–199.

Smith, J., Wilson, S. B., Banks, J., Zhu, L., & Varma-Nelson, P. (2014). Replicating peer-led team learning in cyberspace: Research, opportunities, and challenges. *Journal of Research in Science Teaching, 51*(6), 714–740.

Smith, M. U. (1994). Counterpoint: Belief, understanding, and the teaching of evolution. *Journal of Research in Science Teaching, 31*(5), 591–597.

Snyder, J. L. (2000). An investigation of the knowledge structures of experts, intermediates and novices in physics. *International Journal of Science Education, 22*(9), 979–992.

Spiro, R. J. (1988). Multiple analogies for complex concepts: Antidotes for analogy-induced misconception in advanced knowledge acquisition. *Center for the Study of Reading Technical Report; no. 439.*

Sullins, E. S., Hernandez, D., Fuller, C., & Tashiro, J. S. (1995). Predicting who will major in a science discipline: Expectancy-value theory as part of an ecological model for studying academic communities. *Journal of Research in Science Teaching, 32*(1), 99–119.

Swan, M. (2005). *Improving learning in mathematics: Challenges and strategies.* Department for Education and Skills Standards Unit.

Teichert, M. A., & Stacy, A. M. (2002). Promoting understanding of chemical bonding and spontaneity through student explanation and integration of ideas. *Journal of Research in Science Teaching, 39*(6), 464–496.

Thorn, C. J., Bissinger, K., Thorn, S., & Bogner, F. X. (2016). “Trees live on soil and sunshine!”—coexistence of scientific and alternative conception of tree assimilation. *PLoS One, 11*(1), e0147802.

Tomkin, J. H., & Charlevoix, D. (2014). Do professors matter? Using an a/b test to evaluate the impact of instructor involvement on MOOC student outcomes. In *Proceedings of the first ACM conference on Learning@ scale conference* (pp. 71–78). ACM.
Treagust, D. F., & Duit, R. (2008). Conceptual change: A discussion of theoretical, methodological and practical challenges for science education. *Cultural Studies of Science Education, 3*(2), 297–328.

Trumper, R. (2001). Assessing students’ basic astronomy conceptions from junior high school through university. *Australian Science Teachers Journal, 41*(1), 21–31.

Turkmen, H. (2017). After almost half-century landing on the moon and still countering basic astronomy conceptions. *European Journal of Physics Education, 6*(2), 1–17.

Van Driel, J. H., Verloop, N., & De Vos, W. (1998). Developing science teachers’ pedagogical content knowledge. *Journal of Research in Science Teaching, 35*(6), 673–695.

Vosniadou, S. (1991). Designing curricula for conceptual restructuring: Lessons from the study of knowledge acquisition in astronomy. *Journal of Curriculum Studies, 23*(3), 219–237.

Vosniadou, S. (1994). Capturing and modeling the process of conceptual change. *Learning and Instruction, 4*(1), 45–69.

Wartono, J. R. B., & Putirulan, A. (2018). Cognitive conflict strategy and simulation practicum to overcome student misconception on light topics. *Journal of Education and Learning (EduLearn), 12*(4), 747–757.

Watt, H. G. (2010). Gender and occupational choice. In J. C. Chrisler & D. R. Watt (Eds.), *Handbook of gender research in psychology* (pp. 379–400). New York: Springer.

Wendt, J. L., & Rockinson-Szapkiw, A. (2014). The effect of online collaboration on middle school student science misconceptions as an aspect of science literacy. *Journal of Research in Science Teaching, 51*(9), 1103–1118.

Wilkowski, J., Deutsch, A., & Russell, D. M. (2014). Student skill and goal achievement in the mapping with google MOOC. In *Proceedings of the first ACM conference on Learning@ scale conference* (pp. 3–10). ACM.

Williams, J. J., & Williams, B. (2013). *Using randomized experiments as a methodological and conceptual tool for improving the design of online learning environments*. Retrieved from: http://ssrn.com.ezp-prod1.hul.harvard.edu/abstract=2535556

Wilson, M. (2009). Measuring progressions: Assessment structures underlying a learning progression. *Journal of Research in Science Teaching: The Official Journal of the National Association for Research in Science Teaching, 46*(6), 716–730.

Wind, S. A., & Gale, J. D. (2015). Diagnostic opportunities using Rasch measurement in the context of a misconceptions-based physical science assessment. *Science Education, 99*(4), 721–741.

Windschitl, M., Thompson, J., & Braaten, M. (2011). Fostering ambitious pedagogy in novice teachers: The new role of tool-supported analyses of student work. *Teachers College Record, 113*(7), 1311–1360.

Wyraští, A. F., Sa’dijah, C., As’ari, A. R., & Sulandra, I. M. (2018). The misanalogical construction of undergraduate students in solving cognitive conflict identification task. *International Electronic Journal of Mathematics Education, 14*(1), 33–47.

Xiong, Y., Li, H., Kornhaber, M. L., Suen, H. K., Pursel, B., & Goins, D. D. (2015). Examining the relations among student motivation, engagement, and retention in a MOOC: A structural equation modeling approach. *Global Education Review, 2*(3), 23–33.

Xu, B., & Yang, D. (2016). Motivation classification and grade prediction for MOOCs learners. *Computational Intelligence and Neuroscience, 2016, 4.*

Zemsky, R. (2014). With a MOOC MOOC here and a MOOC MOOC there, here a MOOC, there a MOOC, everywhere a MOOC MOOC. *The Journal of General Education, 63*(4), 237–243.

Zhu, M., Sari, A., & Lee, M. M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014–2016). *The Internet and Higher Education, 37*, 31–39.

Zimmerman, B. J., & Schunk, D. H. (2011). Self-regulated learning and performance. An introduction and an overview. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 1–12). New York: Routledge.

Zohar, A., & Aharon-Kravetsky, S. (2005). Exploring the effects of cognitive conflict and direct teaching for students of different academic levels. *Journal of Research in Science Teaching, 42*(7), 829–855.
SUPPORTING INFORMATION
Additional supporting information may be found online in the Supporting Information section at the end of this article.

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