# A Systematic Review of Research on Personalized Learning:

# Personalized by Whom, to What, How, and for What Purpose(s)?

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## Abstract

Teachers, schools, districts, states, and technology developers endeavor to personalize learning experiences for students, but definitions of personalized learning (PL) vary and designs often span multiple components. Variability in definition and implementation complicate the study of PL and the ways that designs can leverage student characteristics to reliably achieve targeted learning outcomes. We document the diversity of definitions of PL that guide implementation in educational settings and review relevant educational theories that could inform design and implementation. We then report on a systematic review of empirical studies of personalized learning using PRISMA guidelines. We identified 376 unique studies that investigated one or more PL design features and appraised this corpus to determine (1) who studies personalized learning, (2) with whom, and in what contexts, and (3) with focus on what learner characteristics, instructional design approaches, and learning outcomes. Results suggest that PL research is led by researchers in education, computer science, engineering, and other disciplines, and that the focus of their PL designs differ by the learner characteristics and targeted outcomes they prioritize. We further observed that research tends to proceed without *a priori* theoretical conceptualization, but also that designs often implicitly align to assumptions posed by extant theories of learning. We propose that a theoretically-guided approach to the design and study of PL can organize efforts to evaluate the practice, and forming an explicit theory of change can improve the likelihood that efforts to personalize learning achieve their aims. We propose a theory-guided method for the design of PL and recommend research methods that can parse the effects obtained by individual design features within the "many-to-many-to-many" designs that characterize PL in practice.

KEYWORDS: Adaptivity, Learning Technology, Personalization, Personalized Learning

**A Systematic Review of Research on Personalized Learning:**

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Educators have historically adapted their instruction to provide differentiated and individualized instruction based on learner needs (Drumheller, 1971; Slavin, 1984; Subban, 2006; Tomlinson, 1999). Personalization is increasingly becoming an aspirational standard in K-12 educational settings (Ferguson, Ginevra, & Meyer, 2001; Grant & Basye, 2014; Great School Partnership, 2015) and in higher education (Brown et al., 2020). A recent review of educational policy (Zhang, Yang & Carter, 2020) confirms that the vast majority of US states have adopted policies to deliver personalized learning opportunities to K-12 students. Whereas policymakers have reached consensus that students should receive a personalized learning experience, policies provide broad latitude to allow schools to define what personalization means and how to implement it (Kallio, et al., 2020; McHugh, et al., 2020). With this flexibility for implementation comes a challenge for those who seek to understand how personalized learning benefits learners: personalized learning (PL) is defined differently in almost every context where it is employed, and this diversity makes it difficult to assess how PL influences learners' educational experience and academic outcomes (AUTHORS, DATE;  Cuban, 2018; Enyedy, 2014; Halverson, 2019).

Within the context of higher education, the pursuit of a major over and above completion of a general education requirement constitutes a student-driven choice of a personalized course plan. Thereafter, however, few policies exist to govern ways that postsecondary education should be personalized. Whereas early briefs acknowledge individual exemplars such as the Online Learning Initiative (Soares, 2011), few such programs span institutions in ways governed by a guiding policy. The Association of Public Land-Grant Universities established a Personalized Learning Consortium in 2013 and provided recommendations for personalized learning through adoption of adaptive courseware (Vignare et al., 2018), but lacks standing or funding to further organize cross-institutional effort. EDUCAUSE, which organizes conversations amongst administrators of information technology in higher education, provides information about trends towards personalization (Alli, Rajan & Ratliff, 2016; Feldstein & Hill, 2016). It also acknowledges the lack of coherent theory and application (Shulman, 2016), however, and projects personalized learning as a future educational development (i.e., two to five years out), in their 2020 edition of their annual *Horizon Report* (Brown et al., 2020).

**Aim: Understand and Organize Efforts Towards a "Grand Challenge"**

The National Academy of Engineering named the development of personalized learning systems a "Grand Challenge" for the 21st century (Ellis, 2009), and researchers from many different disciplines have taken aim at different features of the grand challenge they describe. The process of personalizing learning requires that a learning environment – whether it be face-to-face vs. digital or human-driven vs. automated – take into account the learner and some combination of their prior knowledge, motivations, goals, beliefs, interests, skills, experience, and culture (and likely other factors) and provide an instructional experience that is responsive to these features in ways that should promote superior engagement in a learning task and performance on it. The dimensions of the PL challenge are myriad and appeal to many different disciplines, which has led to a large and disparate body of research on personalized learning.

Our aim in this paper is to appraise the PL research literature to systematically investigate who is conducting research on personalized learning, what features of the personalized learning process have been investigated, and whether investigations into personalized learning align to theoretical assumptions about the learning process. At present, the research base on personalized learning is beset by the complexity induced by policies that promote implementations that are free to vary the number and types of components they involve to personalize a learning experience. Any attempt to summarize the effect of personalized learning on the learner experience, learning process, or academic performance achieved is thus at risk of inducing a *jingle jangle fallacy* (Gonzalez, MacKinnon, & Muniz, 2020) where many different types of personalized instruction are conflated under a single, insufficiently precise label of personalized learning. As a result, educators who wish to derive these perceived benefits for their students may adopt an instantiation of personalized learning that bears similarity in name, but varies in its implementation from past programs, and thus fails to confer promised benefits to students.

Perhaps in an effort to limit the risk of a jingle jangle fallacy, the sole prior systematic review of research was limited in scope to studies explicitly described as personalized learning with technology, and included only 70 studies (Xie et al. 2019). Xie, Chu, Hwang and Wang (2019) provided an initial consideration of the characteristics of learners and task engagement events that inform adaptivity in technology-based learning environments, and offer a general synopsis of the kinds of outcomes that personalized learning designers targeted. They noted a tendency for these design approaches to achieve positive effects on outcomes spanning affect, cognition, behavior, skill, and performance, among other variables. However, this review relied upon the very general conceptualization of learning provided by Bruner's (1966) model of constructivism, and ultimately made little effort to examine how instantiations of personalized learning are intended to accommodate learner characteristics through design, whether such design processes are informed by educational theory, or how design choices affected achievement of targeted learning outcomes. This lack of theoretical alignment contrasts with research syntheses that were not undertaken as *systematic* reviews but apply a more complex theoretical conceptualization to evaluate adaptive design approaches (e.g., Aleven et al. 2017, Plass & Pawar, 2020). Thus, limited inferences can be drawn about the ways Xie et al. (2019) observed and clarified how personalization achieves effects. In addition, the authors' appraisal of these studies failed to make evident the common implementation of personalized learning in schools, wherein personalized learning often comprises multiple design elements aimed at accommodating multiple learner characteristics, and targeting multiple outcomes in a many-to-many-to-many fashion. In the current systematic review, we grounded our appraisal of personalized learning to a classical instructional design paradigm, and then examined how instructional design might be personalized based on theories of learning that consider the characteristics of the learner, learning processes, and the specific outcomes that instructional tasks are designed to achieve.

In the personalized learning design process (AUTHORS, DATE), any effort to personalize learning must be based on a classic (i.e., non-personalized) instructional design paradigm wherein a learner arrives to a learning environment that is designed to achieve a specific learning outcome, engages in learning, and is assessed on their mastery or achievement of the targeted outcome. The personalization of this learning environment, beginning with an appraisal of one or more features of a learner, must inform the way a learning environment adapts the learning experience through one or more changes from a base mode of instruction. This selection of a learner feature to which the environment should adapt should be motivated by the desire to obtain an educational outcome (Figure 1). The model we propose mirrors the process models that commonly guide decision making in design processes, especially when information stored about users informs the programming logic that delivers the learning experience (Beese, 2019; Reigeluth et al, 2015). We further illustrate the types of learner characteristics that may act as triggers to personalize the learning environment (Figure 1, bottom left) and ways that learning theories propose these characteristics influence design considerations (Figure 1, bottom middle and right).

In order to provide a context for a theoretically-guided systematic review of the PL research literature, we first provide an overview of the many definitions of personalized learning proffered by government, foundations, organizations, companies, and educational theorists, then describe the policy context that promotes the adoption of personalized learning. We then summarize the educational theories relevant to the personalization of learning and proceed to report our systematic review process and the results it produced as they reflect the ways researchers consider the learner, the PL design process, and the learning outcomes it is designed to achieve.

**INSERT FIGURE 1 ABOUT HERE**

## Definitions of Personalized Learning Vary

Personalized learning (PL) has emerged as a promising instructional practice to address the diverse needs of learners in recent years (e.g., Pane et al., 2014). Many definitions have been published to define PL by government offices, educational policy organizations, educational foundations and initiatives, influencers, and researchers. The most commonly referenced definition was provided in 2010 by the U.S. Department of Education Office of Educational Technology, which defined personalization as "instruction that is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners" (US DOE, 2010). Table 1 includes the list of additional definitions which are commonly cited by schools that enact personalized learning initiatives and provides evidence of the diversity of components within and between definitions. A close read of the definitions in Table 1 would reveal that the features included across definitions of personalized learning vary considerably, and that this variation spans the learner characteristics to be accommodated, design elements meant to accommodate them, and outcomes that personalization efforts are intended to achieve. We summarized the relative frequency of these elements across definitions in Table 2. The majority of personalization efforts were centered around identifying and accommodating students' "interests" and "needs," though few additional details were offered to operationally define these terms. Definitions included myriad design approaches to accommodate learner characteristics, including pace, delivery approach, coverage, sequence of instruction, as well as methods of scaffolding, delivering and assessing mastery of content. The learner outcomes that personalized learning could target spanned motivation, skill, and achievement, and not all definitions clearly defined an aim. Perhaps the most salient feature of this thematic representation of personalized learning was the complexity endemic in the definitions. With the exception of a very general definition provided by Cuban (2018), every definition included more than one learner characteristic, design component, and/or learner outcome. This suggests that implementations of personalized learning are likely to be complex, where the effects of multiple design factors may need to be parsed or interacted, and parallel analyses may need to be conducted to examine effects on discrete variables amongst those targeted in a design. This complexity induces challenges for the systematic study of personalized learning, as enacted in authentic educational settings.

**INSERT TABLE 1 ABOUT HERE**

**INSERT TABLE 2 ABOUT HERE**

## From Definition to Policy to Implementation

In the context of educational practice, the varying definitions of personalized learning are accommodated by policies that govern the funding and implementation of efforts to personalize learning from the national to the local level. In the United States, the Every Student Succeeds Act (ESSA) of 2015 provides states with guidance and funding related to PL and includes ten references to PL under four titles; the U.S. law, however, does not clearly define how to operationalize PL (Zhang et al., 2020). Zhang et al.'s (2020) review of state ESSA plans revealed that 33 states included guidelines related to PL, but there was great variability across state plans regarding the definition of PL and the operationalized components. Data collected by researchers who investigated implementation in states that prioritized PL such as Wisconsin give an indication that the PL initiatives school leaders enact often are chosen to leverage extant resources in schools. These implementations appear pragmatic, though they may not align fully to recommendations provided by educational designers and policymakers (Kallio, et al. 2020). Large scale evaluations by RAND (2014; Pane et al., 2014) make clear that PL implementations achieve many positive effects, but also note that initiatives are beset by implementation challenges that can diminish effects. One key conclusion of the RAND report was that PL is likely to be more effective when design and implementations draw upon educational theory.

**Conceptualizations of Adaptivity and Personalized Learning**

Policies that define and stipulate the criteria for a school's initiative to be classified as PL are written in order to provide guidance and flexibility. Schools can adopt one or more of many potential methods of personalization in order to comply with these broad criteria and achieve eligibility for the funding and incentives policies provide. Because of this flexibility, PL programs vary substantially in the amount and combination of features they include. Typically, researchers systematically vary these features, record findings, and build an evidence base and theory that substantiate how components of instructional designs affect learning and achievement. These multi-component designs of PL in schools yield comparisons between programs comprising multiple features, which makes comparative analysis to achieve the causal inference necessary for theory building particularly difficult. If we are to attempt to explain how personalized learning confers benefits to students, a precise taxonomy of critical components of PL to be studied is needed. Such a taxonomy would make clear the systematically testable assumptions about the way that individual personalized learning design choices and their combination can accommodate specific learner characteristics and impact individual outcomes. To build such a taxonomy, we first consider the theoretical literature on adaptive technologies, a theory of personalized learning, and then turn to the broader set of learning theories that may be applicable to personalization.

### ***Appraising the Dimensions of Adaptivity in Learning Technologies***

When considered in the context of learning technologies, those who design for adaptivity undertake such efforts by appraising the common difficulties that learners encounter with a focal subject or task, the inclusion of a pedagogical decision that is based on one or more characteristics of the learners who engage in the task, and a system to interactively respond to learner actions (Aleven, Beal & Graesser, 2013). Because a system can adapt to one or more phenomena, the presence and extent of adaptivity is best understood as lying on a continuum. For example, Aleven, McLaughlin, Glenn, and Koedinger (2017) provided a dimensional grid to organize the ways that designers of adaptive learning technologies intend to support learners, drawing upon empirical literature that examines learner engagement and performance when using adaptive platforms. Thereafter, their model described approaches to further improve aspects of instruction by iteratively collecting and considering data from studies with cohorts of learners, as well as how to instantiate design changes.

These dimensions of adaptivity included the learner characteristic(s) to which the technology adapts the learning experience, and comprised (1) prior knowledge or demonstration through in-task performance that knowledge is increasing, (2) errors made and strategies employed during a task, (3) students' motivation and affect, (4) the degree to which they engage in metacognition, and self-regulated learning via strategies and effort, and (5) the controversially labeled "learning style" that an individual reports. While extensively researched, the validity of this last characteristic remains in question and might be best reframed as a learner's *preference* to learn in a specific way (c.f. Aleven et al. 2017; Kirschner and Van Merrienboer, 2013).

Additional models of adaptive learning broaden the consideration of learner characteristic through the lens of sociocultural theory (Plass & Pawar, 2020). These include learner characteristics that derive from distal layers of a learner's ecological system and factors such as a learner's social milieu, cultural context, as well as the ways that the factors influence students' beliefs about and ways they engage in learning. Specifically, these factors may manifest during tasks to influence the way students' identity, self-perceptions, and feelings of agency and relatedness influence engagement. Plass and Kaplan (2016) further drew attention to ways in-task engagement may induce emotional responses and how tasks might be designed to adapt and accommodate these processes.

The way that developers design learning tasks to accommodate learner features involves multiple layers of consideration, as described by Aleven et al. (2017). At the most general level, the inclusion of content may rely upon considerations about the social and cultural beliefs that learners may bring to a task and how these considerations might lead them to engage with features of content. Thereafter, designers often undertake a *cognitive task analysis* (Clark, 1996) to consider the nature of the learning task and the implicit cognitive (and often metacognitive;

e.g., Aleven et al., 2016) processes employed by students. More recently, designers and researchers have begun to consider learners' motivational (AUTHORS, DATE) and emotional responses during engagement with learning tasks (Plass & Kaplan, 2016). These paradigms can further inform how tasks might be developed to be responsive to such in-situ processes.

When considered from the developer perspective where loops of code that deliver a learning experience are nested within one another, learning technologies can be designed to adapt to these characteristics and events during the design of the environment, the tasks within it, or the specific steps that are completed during tasks (i.e., "design loop, task loop, step loop"; Aleven et al., 2017). Design loop adaptivity spans many learners and involves using data from these learners to adjust the design of the overall environment. This loop does not personalize the experience for individuals, but does lead to future versions of a task that are more capable of doing so. Task loop adaptivity refers to the selection of tasks based on learner characteristics, such as the level of knowledge they possess about a topic, and the likelihood they will benefit from engaging with one task over another. This is common to the design of intelligent tutoring systems (Koedinger & Aleven, 2007) that optimize students' progress through a sequence of units of mathematics based on students' demonstration of prerequisite skill mastery. Task loop adaptivity may also be used to present students with an activity or a representation of a phenomenon that is thought to be the most helpful to students who possess a particular level of prior knowledge, or an identified deficit in such knowledge (e.g., providing worked examples then problem solving opportunities, instead of a faded scaffolding approach; Salden et al., 2010). This kind of task loop adaptivity is critical to providing appropriate learning experiences that support learners with lower prior knowledge and to avoiding the induction of an expertise reversal by over-scaffolding high prior knowledge learners (Kalyuga, 2007). Step loop adaptivity refers to the consideration of students' actions when completing attempts at problem-solving steps within a larger task, and involves the provision of correctness feedback, hints, and other problem-specific support to learners. This form of adaptivity is central to many classes of adaptive software systems including intelligent tutoring systems. When compared to non-adaptive versions, these adaptive learning technologies largely demonstrated superior levels of desired learner engagement and performance (Aleven et al., 2017). These considerations primarily have been applied to learning technologies; however, they can be more broadly applied across any learning environments wherein educators aim to provide more adaptive instruction (c.f., Holstein et al., 2020).

### *Plass's Taxonomy of Adaptivity for Learning*

Plass (2020; Plass & Pawar, 2020) provided a taxonomy of the design space in which instructional designers aim to personalize learning to student characteristics and focused on the variables that should be considered in this process. He highlighted the common adaptive instructional approaches used to support various students, including *differentiation* to accommodate students' interest, prior knowledge, and preferences, as well as *individualization* to accommodate students' degree of special need or a specific level of skill or ability by altering a learning progression. He further distinguished the adaptive practices that accommodate an enduring feature of the learner from the sensitive events that occur during learning that provide information about the learner and engagement within the learning context, which together can inform adaptivity. This *responsive system* approach includes those that adjust the difficulty or pace of problems to adapt to the knowledge or skill mastery that a learner demonstrates, and can be used to promote efficient learning. These responsive systems are programmed to be adaptive and contrast the *adaptable* environments that place learners in an agentic, autonomous role by providing choices to direct their own course at key points in learning tasks (e.g., Harley, Lajoie, Frasson & Hall, 2017). Plass acknowledged that several variables may inform personalization, including cognitive, motivational, affective, and socio-cultural variables, which largely overlap with the specific variables displayed at the bottom of Figure 1. Key to Plass's taxonomy of adaptivity is a set of considerations that would guide the design of a personalized learning design choice: the designer must determine (1) whether a variable is sufficiently relevant to the achievement of a learning outcome, (2) whether there is sufficient variability across learners that designing the environment to accommodate these levels is worthwhile, and critically, (3) whether educational theories and empirical evidence have identified an effective way of leveraging that variable through a design choice that reliably improves the learning outcome. Making determinations in response to the first and second considerations require only that a variable be identified and measured in order to weigh its candidacy. Responding to the third consideration is far more challenging and requires an awareness of the theories and evidence advanced by educational psychologists and learning scientists about the ways that individual learner characteristics affect learners' tendency to engage in particular ways during learning, as well as the ways that engaging in tasks of certain designs benefit learners differently.

### *An Example of Personalized Learning Theory: Context Personalization*

One very specific theory of personalized learning is *context personalization* (AUTHORS, DATE), a method which differentiates learning to accommodate students' interests by placing the learning task in the context of students' area of interest. This method leverages students' situational interest (AUTHORS, DATE), and their depth of knowledge about the problem context (AUTHORS, DATE) in order to produce superior performance on learning tasks in mathematics, and more efficient rates of problem completion and skill mastery. Whereas context personalization provides a framework for accommodating one of the reasonably stable characteristics of a learner (i.e., out of school interest), the dimensions of context personalization are multiple, and require that designers consider which interests should be accommodated (i.e., sports, games, shopping, cooking are common; AUTHORS, DATE), how fine-grained the personalization should be (i.e., should a student interested in basketball receive only basketball content versus many sports), how deeply the problem should leverage the problem context (i.e., passing references to basketball teams and terms vs. selecting a basketball phenomenon that illustrates an equation; AUTHORS, DATE), and whether the student should be afforded any ownership of the problem (e.g., the students' ability to name a player or team; Høgheim & Reber, 2015 or author problem content; AUTHORS, DATE). This single approach to personalizing a task aligns to industry definitions of personalization but makes clear that any single method of personalization requires multiple design choices and that each requires evidence to suggest their appropriateness for accommodating a single learner feature. Multi-component methods of personalizing learning that are commonly adopted in schools thus need to be designed with multiple learning theories in mind and in response to a specifically selected set of learner characteristics that are to be accommodated.

## Learning Theories Relevant to the Personalization of Learning

Though not explicitly developed to inform the personalized learning design process, many theories of learning focus specifically on the way that one or more learner characteristics influence the way that individuals engage during learning tasks, how they may benefit from learning tasks that include (or avoid) certain affordances or activities, and how these characteristics and subsequent engagement in learning lead to learning outcomes. When these learning characteristics are considered as resources to be leveraged through instructional design, the learning theories becomes highly relevant to the personalized learning design process. Table 3 provides a brief overview of the theories of cognition and motivation that can provide conceptual grounding to those who wish to personalize learning to learner characteristics in service of obtaining targeted outcomes. We aim to distinguish individual theories within the areas of cognition and motivation relevant to personalization and further acknowledge that others have elaborated on relevant sociocultural processes (c.f. Plass & Pawar, 2020).

**INSERT TABLE 3 ABOUT HERE**

The refinement of context personalization (AUTHORS, DATE) serves as a running example of the way that learning theory can be used to guide efforts to personalize learning, and how personalizing learning opportunities in subjects such as mathematics to a student's out-of-school interests can improve student learning and also provide evidence to refine learning theory. Context personalization is a common instructional practice that has been employed with the goal of providing students with a motivating contextualization of a learning task (e.g., Cordova & Lepper, 1996), and one that may give them the opportunity to connect a problem scenario to a familiar context wherein they might draw upon the funds of prior knowledge they have developed as they engage their out of school interests (Gonzalez, Moll, & Amanti, 2006). Research into the methods by which context personalization achieves its effects has made clear the relevance of both cognitive and motivational theories to improve context personalization methods. For example, the benefits of personalized learning were observed to differ based on the depth of the prior knowledge that the problem was designed to activate from students' understanding of their out-of-school interests (AUTHORS, DATE). AUTHORS discovered that matching problem depth to students' depth of engagement with their interest influenced students' performance in personalized math problem-solving tasks, which led to an important design principle in context personalization: the problem could either draw on students' informally acquired *funds of knowledge* (Gonzalez, Moll, & Amanti, 2006), or unintentionally induce an *expertise reversal effect* (Kalyuga, 2007). Similarly, AUTHORS (DATE) examined how matching problem contexts to student interests' in sports, games, fashion, technology, and shopping influenced their situational interest (Hidi & Renninger, 2006) in the problem solving tasks, and found that problems that triggered and maintained student interest conferred greater benefits to in task and later performance, as well as later individual interest in mathematics.

A second major aim of this review is to examine how the selections of learning characteristics, personalized learning design choices, and targeted academic outcomes align to relationships posited by theories of learning. Table 3 provides an overview of a sampling of learning theories with cognitive, metacognitive, motivational, and affective elements that are likely to align to the conceptualizations on which studies of PL rest. This should not be viewed as an exhaustive list, but rather an illustrative set we pose *a priori* and later consider as lenses through which the relations amongst learner characteristics, design elements, and outcomes that emerge from the corpus of studies we reviewed might be conceptualized.

**The Theory-to-Research-to-Practice Problem**

In a special issue of *Education Week,* Herold (2017) proposed an argument against personalized learning, claiming that it is a poorly defined educational movement funded by the educational media industry and powerful non-profit foundations. He proposed that personalized learning (1) is overhyped and lacks a research base that justifies enthusiasm, (2) is bad for teachers and students due to implementations that aim to empower student choice in 1-to-1 student to device settings, which typically devolve to behavioristic instructional paradigms and the reliance on algorithm-driven, decontextualized learning experiences, and (3) relies on past student data to inform the personalization process and promotes risks prioritizing the generation and mining of student data over concerns regarding privacy risks and the potential beneficence of such research. These arguments are corroborated by leading educational policy researchers from major U.S. universities (e.g., UCLA) and corporations (e.g., RAND), as well as administrators of large school districts, and educational technology researchers (e.g., Cuban, 2018) and proprietors (e.g., Google).

The central critique that underlies these arguments is that the conceptualization of how learning is to be personalized is underdeveloped, and that "unresolved pedagogical tensions" undermine the personalized learning movement (Herold, 2017, p. 5). The lack of specificity undermines teachers' and technologies' delivery of learning opportunities, and students' experiences during learning. The persistent recommendation is that more and better research be conducted to understand how personalization efforts influence learning, and what conditions must be present in the student and the environment for personalized learning to obtain its promised effects on educational outcomes.

**The Current Systematic Review**

This paper is designed to answer the following research questions: (1) Who comprises the research communities that produce scholarship on personalized learning?; (2) What populations of learners have been studied as they engage with PL resources, in what contexts, and with what methods?; (3) What learner characteristics, design elements, and learning outcomes have been investigated in studies of personalized learning?; (4) How do researchers' personalization efforts relate to the outcomes they target?; and (5) Under what conceptualizations or operational definitions do researchers design personalized learning and observe its effects? Our overarching aims for the systematic review are to summarize these findings to determine the degree to which the answers to the above research questions are congruent across research communities, despite wide variance in the way PL is defined, and align coherently to theories of learning and thus have potential to converge on a consensus conceptualization and the development of a theory of personalized learning.

## Methods

Utilizing PRISMA guidelines (Liberati et al., 2009), we searched the academic literature spanning the years starting at 2010 (i.e., when personalized learning was formally defined by the U.S. Department of Education) through 2018. Databases systematically searched included ERIC, PsychInfo, and IEEE (see Figure 2). We included in our search the "gray literature" wherein papers that are publicly available but not formally published (i.e., dissertations, theses, and reports) were returned by search engines to avoid a file drawer problem induced by potential publication biases. A search of the terms "personalization", "personalized learning", and "personalized instruction" in titles, abstracts, subjects, and keywords was replicated across each venue.

This set of searches returned 1585 records (1372 unique) comprising journal articles (*n*=718), dissertations and other grey literature (*n*=131), and conference proceedings (*n*=523). Conference proceedings were thereafter constrained to the most highly cited conferences per Google Scholar reports (*n*=13 conferences), resulting in 97 papers (see Tables S1 to S3). In total, 992 full-text articles were screened for eligibility. The following criteria were required for inclusion: (1) published between 2010-2018, (2) empirical studies with descriptions of methodology, analyses, and results, (3) explicit reference to an educational aim (i.e., to remove design and development projects conducted with an aim to develop a platform but not to test its effects), and (4) PL must have been a current aim and could not be referenced only as a "future direction" for the research. This evaluation was undertaken by two independent reviewers and inter-rater reliability was evaluated to confirm sufficient levels of agreement on each of the last three criteria. Kappa coefficients were calculated for determination of an empirical study ($\kappa = .83$), with an educational aim ($\kappa = .91$), and that examined PL within the scope of the study ($\kappa = .72$). This screening of the literature yielded a corpus of 355 unique sources that were forwarded to the review stage of the analysis (See Table S4).

Thereafter, feedback provided by experts in personalized learning elucidated a gap in the search of conference proceedings wherein some of the most prominent venues for scholarly research on personalized and adaptive learning technologies were not included in the indexes searched by the IEEExplorer tool we used to engage in a systematic search. We thus conducted a hand search of the conference proceedings for the term "personalized learning," as well as cognate terms used to described "adaptive learning," "mastery learning," and "smart learning" environments, as recommended by an expert reviewer. This additional search yielded 240 additional hits, 215 of which were unique after duplicates were removed. Of these, 21 met criteria imposed during screening and were added to the analyses. We subsequently considered a revisitation of the systematic searches of the ERIC, PsychInfo, and IEEE indexes, but the nature of these additional search terms proved problematic when applied to such large corpuses of literature. Each of the terms refers not only to learning environments that are personalized or adapted, but also refers to additional phenomena related to education, but unrelated to design efforts to personalize learning. For example, inclusion of "mastery" as a search term along with learning produces thousands of additional matches due to additional definitions related to student goals (e. g., mastery orientation). "Smart" was problematic for similar reasons, and the term "adaptive" is broadly applied to assessment instruments and approaches that are unrelated to personalization efforts. We thus retained our initial approach to search of these literatures and return to the challenges imposed by language to describe personalized learning in the discussion section.

Our review of the eligible studies included contextual, structural, methodological, and conceptual components. To determine the academic origin of PL research, articles were reviewed for the academic affiliation of the author, the geographic location, and the publication venue of the source (i.e., Research Question 1). The design context of personalized learning to be examined was captured by recording the academic subject and educational level, as well as the variety of learning technology or non-technological context in which the PL was conducted (i.e., Research Question 2). Papers were next evaluated to identify the learner characteristics that were the subject of personalization efforts (e.g., interest, preference, prior knowledge, see Figure 1). Papers were further reviewed to identify methodological details related to participants (e.g., sample size, age, gender, ethnicity) and the dependent variables which PL implementations were hypothesized to effect (i.e., Research Question 3). Finally, the conceptualization of the PL design under investigation was observed by capturing the authors' verbatim definition, descriptions of PL in the text, and any citations of a formal definition of PL (i.e., Research Questions 4 and 5).

**INSERT FIGURE 2 ABOUT HERE**

## Results

Based on the classifications of design elements of the studies we reviewed, we present descriptive results that address four research questions about the source and design of studies of personalized learning. In each section, we also conduct inferential analyses to address the first overarching aim of the paper and evaluate whether the descriptive statistics differ significantly across PL research communities. We then address our second overarching aim – appraising the alignment of studies of PL to assumptions derived from theories of learning.

## Research Question 1: Who Studies Personalized Learning?

### *Geographic Regions*

We first examined the geographic placement of the institutions where PL researchers affiliated in order to examine whether the research base on PL includes a representative sample of investigator perspectives and participating samples. Thereafter, we examined the location of scholarship from within the United States, in order to examine whether research on PL overlaps states with policies governing implementation of PL. Figure S1 illustrates that more researchers investigated PL in the United States, China, and the United Kingdom, but also that PL was investigated with populations on all inhabited continents, if sparsely. Within the United States, the majority of research is produced by researchers who affiliated with institutions in the Southwest, Midwest, and Northeast regions of the country. This research activity largely overlapped with the implementation of PL practices governed by states with formal policies. Research activity was ongoing in all states with PL policies in place, with the exception of Alaska and was heaviest in states with broad implementations (e.g., Wisconsin and Vermont).

### *Academic Disciplines*

The majority of research on personalized learning was led by researchers who affiliated with education units. Educational researchers composed a slight majority of the population of lead authors, with scholars from many other fields leading research on personalized learning, including substantial numbers of researchers who affiliated with Engineering and Computer Science units. Thereafter, researchers who investigated personalized learning spanned information technology, informatics and information sciences, psychology, business, communications, and physical and library sciences, among other disciplines (Figure 3). We augment these findings with the acknowledgement that, across the studies reviewed, it was evident that personalized learning research efforts were the product of collaborative and interdisciplinary teams, with many comprising multiple scholars with complementary expertise spanning multiple academic disciplines. Thus, although we catalog only the first author's home unit in the figure, it is indeed the case that it was quite typical for a large number of researchers to contribute to a single study. We return to this in the discussion section where we consider the kinds of effort and expertise that are required to examine how PL designs achieve effects on outcomes across populations and contexts. The diversity of scholars who led evaluations of personalized learning to improve learning outcomes confirms the need to examine how scholars formed in different academic traditions engage on the topic and whether their focus and language align.

**INSERT FIGURE 3 & S1 (link) ABOUT HERE**

***Publication Venues***

The majority of personalized learning publications appeared in indexed research journals. However, the preponderance of research on PL conducted by researchers from Engineering and Computer Science and related disciplines are unlikely to be discovered by those who only search these indices, as their fields prioritize conference proceedings as a primary outlet for scholarship (See Figure S2). Any synthesis of PL research must draw upon both journal and conference papers in order to fully represent the larger community of scholarship. A chi-square analysis confirms that engineering and computer science disciplines disproportionately publish in conference proceedings compared to scholars affiliated with Education units, $\chi^2$ (2) = 38.66, $p <$

.05. Further, the volume of unpublished dissertations and reports in other venues cannot be discounted. Because PL has become a common inclusion in policies that govern educational practice, a considerable number of research reports were published in venues that are not indexed at all and would require a broader search of the literature, perhaps involving the use of Google Scholar or other platforms that include citations of popular media.

**INSERT FIGURE S2 (link) ABOUT HERE**

## Research Question 2: What Populations of Learners Have Been Studied as They Engage with PL Resources, in What Contexts, and with What Methods?

In order to understand the implications of personalized learning for learners, it is essential to understand who the individuals are who engage in personalized learning, and under what conditions learners engage in these PL tasks. Figure 4 illustrates that PL was broadly studied across the continuum of K-12 and higher education populations, with limited investigation of its effects for younger children or for adults in graduate, professional, workplace, or informal settings.

**INSERT FIGURE 6 ABOUT HERE**

### *Learner Populations and Method of Instructional Delivery*

PL instruction was primarily delivered using digital platforms; more than 80% of implementations required access to some form of learning technology to engage in PL in fully digital or hybrid delivery format (see Figure S3). However, 37% of the PL implementations evaluated also spanned not-exclusively-technological settings, which underscores the importance of expanding research syntheses beyond those that solely consider findings from digital settings (e.g., Xie et al., 2020). Our findings suggest that PL instruction was more often used as a supplemental, diagnostic, or reactive educational approach, as opposed to a primary mode of instruction. The majority of studies focused on the adaptive nature of PL and its reliance on the collection of student data to provide individualized and differentiated instruction, though the number of studies (40%) that investigated PL instances that were deployed as the primary mode of instruction illustrate the breadth of adoption of PL, and reliance upon it, in authentic educational environments, as described in policy research (Zhang et al., 2020).

**INSERT FIGURE S3 (link) ABOUT HERE**

### *Academic Domains*

In addition to the span of digital and classroom instances and primary and supplemental modes of instruction, PL was implemented in many different academic domains and school subjects. As illustrated in Figure S4, STEM domains such as science, computer science, and mathematics that involve proportionally more problem-solving tasks than other academic subjects compose the majority of contexts investigated by PL researchers. Domains also included English and other language courses, and 12% of the studies conducted investigate PL designs that spanned multiple components of an academic curriculum. This latter phenomenon aligns with PL definitions and policies that recommend personalization designs should incorporate multiple components and be implemented at a school-level in order to allow students to set goals, make choices, and pursue learning paths (Kallio, et al., 2020).

**INSERT FIGURE S4 (link) ABOUT HERE**

## Research Questions 3: What Learner Characteristics, Design Elements, and Learning Outcomes Have Been Investigated in Studies of Personalized Learning?

The second overarching aim of this systematic review was to examine not only the contexts in which PL research was being undertaken but also the definitions of PL and theoretical conceptualizations that guided the implementation of studies. To assess these features of the extant research, we began by analyzing the definitions of PL that researchers stated in their publications and thereafter developed a taxonomy of PL design features in order to compare them to theories of learning. Figure 5 includes a series of word clouds that represent the proportional inclusion of words in passages of text from research publications in which researchers defined personalized learning. We conducted an overall analysis of the entire sample of studies we reviewed and further broke down our sample into the research communities that emerged in analyses conducted to address Research Question 1 (see Figure S3). The prominent vocabulary found in the overall sample largely aligns with vocabulary used in formally established definitions of personalized learning (see Tables 1 and 2). However, authors largely failed to align their operational definitions to these formal definitions via citation: less than 6.5% formally cited any of these definitions of PL. When considered by the academic home of lead researchers, the language comprising definitions of PL differs markedly across units. Definitions across all units included considerable focus on the *individual* and their *needs,* as well how each are *different.* Researchers from Education units additionally focused on the learners' *interests* and *goals*, as well as the *environment* in which PL occurred. These researchers also were unique in their proportionally higher inclusion of *teachers* within definitions of PL. Alternatively, researchers from Engineering and Computer Science units focused on *system(s)* that *adapt* or are *adaptive*.

**INSERT FIGURE 5 ABOUT HERE**

### *Learner Characteristics*

Figure 6 illustrates that, as proposed in descriptions of the design of adaptive learning environments (Aleven et al., 2017; Plass, 2020; Plass & Pawar, 2020), the majority of PL designs were adapted to students' prior knowledge and preparedness to learn, adjusted features of the learning tasks during learning based on ongoing performance, or were adapted to accommodate learners' preferences and interests. Perhaps more problematically, the fourth most common learner characteristic that PL designs accommodates was an individual user's "learning style" (see Paschler et al., 2008 for a review of the construct). Aleven and colleagues (2017) provided a thorough overview of the empirical and theoretical arguments against the existence of learning styles and thus dismissed them as a relevant construct to be accommodated by instructional design. They argued against their inclusion and revoiced that the existence of "learning styles" or any such implications for learning have been largely debunked through empirical testing (Kirschner, 2017; Pashler et al, 2008; Willingham et al., 2015). We revisit this more extensively in the discussion.

In addition to examining the overall prevalence of accommodations of learner characteristics in the PL designs under examination, we conducted analyses to determine whether the focus of PL designs differed by the academic domain of the lead researcher. Chi-square analyses confirmed that there were significant differences in the proportional focus on individual learning characteristics between Education, Engineering, Computer Science, and other research communities $\chi^2(9) = 47.3505$, $p < 0.00001$. Our findings show that Education researchers were disproportionately focused on studying PL designs that accommodated students' interests compared to other communities (see Figure 6 and Table 4). Engineering and Computer Science researchers investigated PL designs that accommodated students' (usually self-selected or self-reported) "learning styles" in 26% and 17% of their studies, respectively. This characteristic is the focus of only 8% of all studies, and only 2% of studies in Education (see Figure 7).

**INSERT FIGURE 6 & 7, TABLE 4 ABOUT HERE**

***Outcome Variables***

Figure S4 (left panel) displays the number of studies that evaluated PL designs aimed at affecting specific student outcomes. Other than those papers that failed to provide sufficiently-detailed reporting – which we revisit in discussion – the most common aim of a PL design was to improve students' performance within the task or on a measure of academic performance. Other common aims of PL designs were to improve students' perceptions of and satisfaction with their learning. A set of studies examined whether PL designs could improve affective or motivational outcomes including efficacy, motivation, engagement, as well as self-reported interest, enjoyment, or positive emotions during learning. A subset of studies evaluated the degree to which PL designs achieved stronger endorsements of the usability of environments and the quality of their implementation. The assessment tools used to substantiate these outcomes included activity within the PL system and assessments in and outside the environment, as well as survey, interview, and observation methods. PL environments meant to affect distal factors included students' grades and disciplinary referrals (Figure S4, right panel). Similar to the differences in focus on learner characteristics by researchers affiliated with different academic units, we again observed differences between academic domains (i.e., our first overarching aim) in their proportional focus on outcomes to be achieved by PL designs under evaluation (see Table 5). Whereas all researchers were primarily interested in PL environments designed to improve academic performance, chi-square analyses of the most common four and seven variables under observation in research conducted across academic units confirmed that Education researchers were disproportionally less focused on improving student satisfaction with or the usability of PL designs (7%, 0% of studies) compared to researchers in other disciplines (14-21%, 7-11% of studies).

**INSERT FIGURE S4 (Link) & TABLE 5 ABOUT HERE**

### Research Question 4: How Do Researchers' Efforts to Personalize Instruction Relate to the Learning Outcomes They Target?

We next built on our analyses that examined the learning outcomes that researchers and designers aimed to impact with personalized learning designs to determine how personalization efforts were associated with learner outcomes. We conducted an additional round of review to catalog instances where researchers (1) designed experiments to test personalized learning conditions against control conditions where no personalization was in place or (2) examined the degree to which students' learning experience involved engagement with personalized learning design features, as well as the relationship between such use and the assessed learner outcomes. Next, we categorized the directions of effect or association (i.e., positive, negative, or none observed) and tallied the number of studies in which such effects or relations were observed. Additionally, we also cataloged instances where researchers collected data on relations between personalization and learner outcomes, but the design of their study was qualitative in nature and thus intended to observe emergent phenomena rather than test inferences. We present stacked bar charts in Figure 8 where the relative height of a bar demonstrates the amount of research that examined how personalization efforts related to learner outcomes. Each bar represents studies that explored a given relationship with those using qualitative methods (i.e., in gray) at the bottom and then a valenced, proportional display of those that found negative causal or associative relations (i.e., red range), no relation (i.e., in yellow), and positive associative or causal relationships (i.e., green range). Results of this display confirm that a substantial proportion of the research was exploratory in nature, and that findings relating personalization efforts to learning outcomes were often emergent in nature. Moreover, researchers tended to adopt correlational designs far more often than experimental ones. Of the designs that inferentially tested relations, we found more positive than negative relations and effects. The distribution of studies across many learner outcomes, however, further demonstrates the diversity of aims held by those who personalized learning, and the paucity of research on any single learning outcome could warrant a meta-analytical treatment to better understand such effects.

**INSERT FIGURE 8 ABOUT HERE**

### Research Question 5: Under What Conceptualizations or Operational Definitions do Researchers Design Personalized Learning and Observe Its Effects?

To answer our final research question, we appraised the language used to define personalized learning comprising the learner characteristics, design features, and target outcomes. Our second overarching aim – to appraise the degree to which PL designs and studies of the align to, might benefit from, and can advance theories of learning – required that we not only examine the raw and proportional frequency of research design features but also the relations among these features within studies of PL. Our first observation was that, despite our intentions to record researchers' references to extant learning theories that informed the PL designs, very few papers provided an explicit theoretical conceptualization about how personalizing to a learner characteristic should achieve an improvement in a process or outcome. Thus, we explored whether an implicit *a priori* consideration of learning theory could be derived by examining alignment to learning theories based on the design elements in PL environments within the studies we reviewed.

In order to examine theoretical associations, we constructed a pair of Sankey diagrams that demonstrate the frequency with which elements were associated in our observed sample. These diagrams appear illustrate the learner characteristics leveraged to target outcomes (Figure

S5), and the variety and frequency of design approaches used to personalize a learning experience to a specific learner characteristic in order to target a specific learning outcome (Figure 9). One critical observation that is not illustrated in these Sankey diagrams but might be inferred from the bottom panel is that many PL designs are intended to achieve multiple outcomes, employ multiple design elements, and accommodate multiple learner characteristics. These many-to- many (to-many) relationships were operationalized in most PL implementations; thus, some parsing is required to deduce the assumptions that led to such complexity.

The first Sankey diagram (i.e., Figure S5) provides a general sense of the magnitude of focus placed on individual learner characteristics and learning outcomes, and the degree to which personalization involved homogeneous or heterogenous assumptions regarding the learner feature that should be accommodated to achieve an outcome. Academic performance was the most common outcome targeted by PL designs, but designs accommodated a heterogenous set of learner features to promote it, including students' prior knowledge and preparedness to learn, learners' preferences and interests, and various "styles" including their self-reported or -selected learning style, cognitive style, or language style. Additional features that were leveraged to improve academic performance included students' demographic attributes, preference of pronouns, personality, learning goal, and interpersonal needs. This pattern of heterogenous accommodation of multiple learner characteristics in the service of a specific target outcome also employed designs aimed to improve affective and motivational outcomes, such as satisfaction, perception, efficacy, and engagement. PL designs focused on improving usability and the performance and implementation of the system also accommodated multiple user characteristics. Homogeneity in characteristics was observed only in the case of promoting interest in learning via PL, which solely accommodated students' stated interests as reported prior to or selected during learning (i.e., in all three of the studies observed).

**INSERT FIGURES S5 (link) & 9 ABOUT HERE**

The second Sankey diagram examines the designs employed by those who produced and evaluated PL platforms and affords an opportunity to inspect the different PL approaches that designers adopted in order to promote learning outcomes and accommodate learner characteristics. This three-step diagram reveals additional heterogeneity in the way that designers accommodated learner characteristics in order to obtain learning outcomes. For example, the most common method of personalizing learning in order to improve performance was to provide an adaptive experience that was personalized to students' prior knowledge (and in the case of adaptable environments, updated demonstrations of knowledge) and other estimations of their preparedness to learn. These design choices appear in the blue blocks in the middle column of Figure 9. This panel clearly demonstrates that designers differed in the methods they chose to leverage information about a student's preparedness to promote additional learning and achievement. The slight majority of PL platforms responded to data about students' preparedness through system-initiated adaptation of the tasks' rigor in response to prior or in-task performance data. For example, these design choices included in the blue block atop the middle column include designs such as intelligent tutoring systems, which relied on estimates of prior knowledge to inform the learner models that adapted problem selection and further informed the task design in adaptable fashion based on updated estimations of mastery demonstrated through in-task performance. The next two blue blocks include those tasks that adjusted rigor only on a preliminary assessment (i.e., without further adaptation based on in-task performance) or on an external data source reflecting prior knowledge or preparedness. Next, the additional color blocks in the bottom panel reveal a complex design landscape where at least one design choice made by developers may accommodate one or more learner characteristics in order to achieve a set of targeted learning outcomes. Continuing the example of accommodating through PL based on preparedness to learn, the other PL designs focused on leveraging prior knowledge to promote academic achievement include provision of choice to learners, who can choose the content, task, and manner of presentation of material, as well as the order and timing they engage with the materials (i.e., Figure 9, yellow block). These yellow features align to design work aimed at providing choice (Patall et. al, 2008), but in the context of research deriving from adaptive software environments that assess prior knowledge, such design choices are known to promote overlearning of a narrow subset of simpler content and avoidance of more challenging content (Long & Aleven, 2011). Long and Aleven (2011) describe demonstrated this tendency to continually revisit topics already studied as leading to perseveration and stagnation, thus slowing progress through self-paced instruction, when such choice is afforded. In addition to adapted rigor and choice provision, a number of different systems adapted the way content was displayed to learners based on their self-reported "learning style" or actions within the environment. Other systems tailored instructions or task framing to students based on data about their personality, interests, or other factors (i.e., green and purple blocks). The red blocks of instructional design features reflect designs that were multi-component and school-wide, where a restructuring of an educational environment was undertaken to accommodate students' preparedness to learn alongside many other factors with the goal of promoting academic achievement and other desirable outcomes. These whole-school approaches often involved the restructuring of the school day to provide flexibility for students, opportunities for blended learning between 1:1 time on a device and classroom activities, and additional opportunities for interactions with classmates, teachers, and staff to work towards developing and progressing through personal learning plans. These school-level designs involve a many-to-many-to-many approach, illustrated by a diversity of paths leading into and out of the red blocks, where the school attempted to accommodate students' preparedness and preferences in service of promoting motivation, engagement, and performance, among other targeted outcomes. Whereas multi-component, school-level interventions understandably may have adopted this complexity in associations across characteristics, design elements, and outcomes, the pattern of complexity that can be observed across other blocks of design elements reveals that designers often anticipated that single PL design choices were likely to achieve multiple-targeted outcomes. We consider these designers' assumptions in light of the assumptions proposed within theories of learning.

## Discussion

From over 375 studies undertaken to investigate the designs and effects of personalized learning, we conclude that those who studied personalized learning from 2010 to 2018 spanned all six inhabited continents, and conducted research activity largely in regions where PL implementations were in place. While the PL research community includes scholars from many academic domains, the bulk of research on PL was led by scholars who affiliated with Education, Engineering and Computer Science units of higher education institutions (i.e., Research Question 1). Learners who engaged in PL designs spanned K-12, university, and adult populations who tended to engage in technology-based environments, many of which were complemented by classroom-based PL activities. These PL designs were most heavily used in mathematics and other STEM domains, but some PL design work was conducted in English, language arts, and other areas of the humanities (Research Question 2). Our second block of research questions served to address our two overarching aims in the paper and examine the degree to which PL designs were found to be associated with the learning outcomes they were designed to target (Research Questions 3 & 4), how well such designs were informed by theories of learning, and how the reliance on theories and inclusion of design elements varied across segments of the PL research community (Research Question 5). Overall, the vast majority of research conducted on personalized learning was exploratory in nature, wherein researchers employed qualitative, descriptive, or correlational designs to examine users' experiences, and the degree to which such experiences related to targeted outcomes. These studies were critical to the earlier phases of the design process where, after a period of ideation, designers tested whether they had developed a product that was usable, whether they delivered a satisfactory experience for their target population, and whether engagement with the product was associated with the aims it was designed to support (Rothwell & Kazanas, 2011). However, this early stage design research fell short of the criteria for evidence necessary to inform research syntheses (Lipsey & Wilson, 2001). Personalized learning was broadly defined and targeted multiple outcomes. This diffused research efforts across criterion variables and slowed progress towards a critical mass of studies that warrants meta-analysis and examination of moderating factors. We return to this topic as we make recommendations for future definition, design, and research, and for now simply acknowledge that the few studies that provided correlational or causal evidence demonstrated more positive relations and effects than null or negative findings. Having established this emerging pattern, we next considered how the designs that produced these relations and effects were conceptualized vis-à-vis learning theory.

**Alignment to Theories of Learning**

One surprising finding in this review is that despite some overlap in the features of operational definitions of PL, researchers seldom substantiated alignment to common definitions of PL, or to learning theories that guided the conceptualization of their study designs. We thus conclude that most PL research was only loosely aligned to formal definitions and theories. Emergent conceptualizations based on research designs further confirmed that researchers varied in their operational definition and conceptualization of how to personalize learning, and that these differences often nested with differing proportional focus by the academic home of the lead researcher. Focal learner characteristics and target outcomes varied across academic disciplines. Educational researchers more often personalized to interest and prior knowledge and expected greater engagement and performance, accordingly; computer scientists and engineers were more apt to personalize to preferences including potentially problematic variables including debunked "learning styles." Further, designers often developed PL approaches that aimed to achieve a diverse set of target outcomes, often with only a single PL design element. In light of these findings, we consider some emergent themes revealed by our analysis, and consider how they relate to a potential way forward where personalized learning aligns more closely to extant learning theory.

**Adaptation to prior knowledge and preparedness to learn is robust and widespread.** Of all PL designs, those that adapt elements of instructional design to data indicating students' prior knowledge and preparedness to learn in order to promote more efficient learning were the most plentiful and the most well aligned to theory and research. The wealth of scholarship on cognitive modeling and the tight connection to classes of educational technologies such as intelligent tutoring systems and other adaptive systems affords ample evidence that leads to the refinement of both theories and implementations of this form of adaptive and personalized learning (Aleven et al., 2017; Plass, 2020).

**Applying multimedia learning principles, not PL to beliefs or "styles" promoted learning; consider the content**. PL designers, especially those outside of education, seemed enamored with "learning styles", and may have been largely unaware of the paucity of evidence for their existence and the preponderance of evidence to the contrary. Additionally, they may not have previously been exposed to the many principles derived by multimedia researchers or the Multimedia Learning Theory that comprises them (Mayer, 2016). Hundreds of studies documented by instructional design researchers confirmed that, often regardless of learner preferences, instructional design that followed specific design principles related to the spacing, contiguity, redundancy, and inclusion of design elements consistently provided benefits to learners who use them. Whereas students' preferences for the way information is presented can differ, evidence from research on learning with multimedia has consistently shown that the nature of the content to be learned was a more important determinant of the way those materials should be displayed to learners than students preference for a modality of presentation. Further, the paucity of evidence of effects of accommodation of "learning styles" on achievement suggests that this design choice is unlikely to yield any of the benefits targeted by PL designs.

**Task framing was popular in PL, but conceptualization varied; consider motivation theory.** In addition to presenting content based on students' preferences, some PL designs reframed tasks by introducing them to learners in different ways depending upon learner characteristics including their personalities, goals, interests, and other factors. Despite a general lack of *a priori* acknowledgement of alignment to them, a number of theories of academic motivation explicitly proposed relationships between goals, expectancies of success, efficacy, and perceptions of the values and costs associated with task engagement, as illustrated in Table 3. Intervention research that examined how reframing tasks for students or asking students to self-generate information about a learning task that pertains to their efficacy for it or reasons they might value it have shown promise in promoting interest, persistence, achievement, and future motivation and behavior (Høgheim & Reber, 2015; Hulleman, Godes, Hendricks, & Harackiewicz, 2009; AUTHORS, DATE, DATE, DATE, DATE). This area of intervention research has become particularly robust, to the point that meta-analyses of interventions afford moderator analyses that can inform the task framing approaches that PL designers intend to provide (Lazowski & Hulleman, 2016) and consider how students will differ in their responses and the ways the benefit from these design approaches (Canning, Priniski & Harackiewicz, 2019; Durik & Harackiewicz, 2007). The adoption of these design choices into PL environments also has potential to catalyze research, especially if implemented systematically and at scale (Sales, et al., 2018) and might further enrich the study of motivational interventions as a result.

**Identity-driven personalization and emergent PL design paradigms; proceed with caution.** While not sufficiently conceptualized by designers nor examined at sufficient scale to afford any conclusions, a number of studies examined learner characteristics that reflected elements of the learners' identity. A number of personalization efforts aimed to adjust the learning task in ways that would enable the student to identify with features of the task. These included personalizing to students' preferred pronouns (Halkyard, 2012), the use of familiar names or places (Kleinman, 2018), storytelling (Armstrong et al., 2016; Haas, 2016), and using information from the students' own lives (Cakir & Simsek, 2010). In addition to funds of knowledge, theorists posed that students also bring to learning tasks their *funds of identity*, internalized family and community resources used to make meaning, and describe themselves (Esteban-Guitart & Moll, 2014). Students' geographical, practical, cultural, social, and institutional funds of identity can inform instructional decisions to help students better connect with content. Whereas some dimensions of identity might be sufficiently canonical or finite that a program could ostensibly collect precise data that reflect students' identity-related values for a variable, and designers could adjust a learning task in ways that incorporate them (e.g., cue students' preferred pronouns, Halkyard, 2012), many aspects of identity and the instruments that would surface them do not produce clear indications of learners' characteristics. This limits how readily such data can be operated upon in designs that aim to produce a PL experience. Tools like family histories (Kleinman, 2018) and self-portraits (Esteban-Guitart & Moll, 2014) can provide insight into students' funds of identity, but are quite complex. Even when learners' individual experiences can be captured, these data will be captured as lengthy descriptions, rather than categorical indicators that can be operated on with scripted logic to adapt features of a learning task. As a result, learners' funds of identity can and should be considered by teachers who can design and deliver instruction that can give students the autonomy and ownership of learning experiences they can make personal (e.g., student-curated collections; Tsybulsky, 2020). However, developers of PL technologies were limited in the way their designs responded to any more than a few, rather simple aspects of a learner's identity. The incorporation of the more complex aspects of identity (i.e. socio-cultural practices) did not lend themselves to the automated logic that underlies technology-based PL designs. Ultimately, extreme caution should be used when considering how to leverage – and avoid misconstruing or misusing – cultural funds of identity in instructional design to avoid marginalization or misrepresentation of minoritized learners. One productive way forward might be to design for "adaptability" (Plass & Pawar, 2020, p. 277) where learners are given the choice of ways they might alter the design or course of a learning task. This design approach aligns to the dimension of ownership that characterizes *context personalization* (Authors, DATE), in which learners select interest areas that can be accommodated by changing the context of a learning task. Placing the learner in the agentic position and using their personal funds of knowledge and identity has also been used to promote self-generated relevance and make meaningful connections in learning (Hulleman, et al. 2017). This design choice avoids potential misses when trying to personalize learning, and can help designers avoid learner *reactance* (Brehm & Brehm, 1981), which may negatively affect motivation and engagement in learning, once induced.

**Implications for Improving Description, Implementation, and Study of Personalized Learning**

The discussion, design, testing, and implementation of personalized learning is beset by challenges with the complexity of a common PL design that attempts to accommodate all learners based on multiple characteristics, with multiple design elements, and to multiple ends. Those who design, study, and employ personalized learning can parse this complexity by adopting more precise language in describing the way learning is made more personal, is adapted, or continues to be adaptable. Thereafter, they can consider how they believe the personalization of a task benefits a learner, and what must be known about the learner to do enact such a plan. This theory of change and its quality can then be appraised for its coherence, both in terms of its alignment to theories about the learning process and its alignment to empirical findings that confirm that a proposed instructional design approach has achieved targeted outcomes for learners in the past. In sum, the study of personalized learning would benefit from a linguistic taxonomy that describes each component of a PL effort, as well as an explicated theory of change that guides design and can inform the study of the assumptions it includes.

**Language and definitions.** Tables 1 and 2 provide a broad overview and thematic alignment of the learner characteristics, design elements, and learning outcomes that an individual may be thinking of when they are discussing personalized learning. This induces risk where two people who aim to discuss PL can mean two entirely different things, arrive at different conclusions about the merits of the approach, each be independently correct, and achieve nothing in their discussion. In order to provide researchers, designers, and practitioners the tools they need to describe PL more coherently and engage in design, appraisal, and adoption more productively, we propose a decomposition of PL into its component forms that involves use of clearer terminology for and connection between classes of learner characteristics, the ways this information is gathered and acted upon in a PL design, and the outcomes that are targeted.

The list of learner characteristics that inform PL designs is staggeringly large. However, Plass and Pawar (2020) and AUTHORS (DATE) proposed organizing frameworks that can group these characteristics according to their cognitive, motivational, affective, and emotional, or sociocultural origins. This organization simplifies consideration and allows designers and adopters to more systematically consider the need of learners that require a personalization of instruction to accommodate them, or how adapting instruction based on what is known about a learner can make their impending experience a more productive or efficient one. When asked about their students' challenges in learning, teachers tend to speak at this level of generality and describe students' preparedness to learn in terms of their prior knowledge or reasoning ability and motivation, tendency towards boredom or frustration that threatens learning and persistence, or their perception of the relevance of topics to their daily life (Turner, Christiansen, & Meyer, 2009). These dimensions of teachers' appraisals align directly to the cognitive, motivational, affective and emotional, or sociocultural processes that educational researchers study. When this is acknowledged explicitly, practitioner-researcher teams can engage with theory, plan design, and contribute back to the empirical evidence base when they carry out instruction that supports learners through personalization (AUTHORS, DATE).

Whereas descriptions of students' assets and needs were more coherently described by the language of educational psychologists, improving description of the way these information are gathered and leveraged requires language from programmers and designers. The common thread across all PL designs was that a program's function (or student's classroom experience) was altered based on a piece of information provided by or about a learner. These details can be provided once at the outset of the task by the learner or another entity, updated during the task when the program appraises a learner's actions or products, or by re-engaging a learner directly. Not all PL programs are embedded in technologies, but all adopt this type of IF-THEN language in their design. Another way that personalized learning might be more clearly described is by noting not just the type of information that informs this IF-THEN, but also whether the *source* of the information is the learner, an external reporter (e.g., a teacher) or repository (e.g., school database), or the system itself (e.g., appraisal of current student skill mastery based on past performance). The source of these data can help establish whether a PL design is one that needs to be setup and informed by a teacher, integrated with other systems (i.e., synced to access school records), or as a standalone instructional tool where all information is provided by the learner. A second design feature is the *timing* of the reporting of a learner characteristic. This describes whether personalization is based on a preliminary, one-time report of a (theoretically enduring, stable) learner characteristic, or whether the system repeatedly adapts the task by recursively updating the data that inform an IF-THEN statement. For example, this distinction can separate PL designs that accommodate students based on an initial report of their prior knowledge (e.g., Reddy et al., 2015) versus a design that constantly adapts the rigor of a learning task based on estimates of their current knowledge state (e.g., Arroyo et al., 2014). It could also differentiate between designs that present content that aligns to learners' surveyed interests in topics (AUTHORS, DATE) versus those that consistently prompt a learner to select a topic they find to be most interesting (Scanlon et al., 2011). Aleven and colleagues (2017) referred to the position of this IF-THEN relationship by its presence on specific "loops" of a program, and Plass and Pawar (2020) drew distinction between environments that are *adaptive* to initial appraisals of learner characteristics versus those that are *adaptable* based on experiences that arise during learning. The timing and frequency with which tasks are re-calibrated to adapt instruction are worthy of distinction, as personalization to a learner characteristic that is malleable and not enduring at a single time point versus personalization on an on-going basis are likely to differ in the degree to which they accommodate learners' knowledge, interests, choices, emotions, and other factors, and achieve different outcomes as a result.

**A theory of change.** Educators and policymakers adopt personalized learning in order to achieve a targeted outcome for learners. They may seek to raise student achievement or motivation to learn, or to instill a sense of agency or satisfaction when engaged in learning. Whereas the desire to achieve these outcomes motivates the adoption of PL, educators and policymakers often lack the resources necessary to determine which PL design is best suited to achieve their ends. This can stem from a lack of formal training necessary to understand how learner characteristics or instructional activities influence the learning process, a lack of transparency about the way design elements deliver and personalize a task, or a combination of the two. Those who select, configure, and deploy personalized learning in authentic learning environments need encouragement to formalize their theory of change, and resources that can help them identify whether research supports their intuition, and whether a model of PL exists that can be adopted to leverage the learner characteristics to deliver the ends they seek (AUTHORS, DATE). Policy briefs encourage and provide guidance to help educational decision makers carry out this kind of planning process (AUTHORS, DATE). However, those who design PL solutions need to align their own materials to such theories of change in order to enable decision makers to understand designs and confidently adopt one that matches their theory of change and is likely to provide the outcomes they seek to achieve.

**A challenge to PL designers.** Informed adoption of PL requires that designers of PL explicitly align their designs to a well-described theory of change, and provide transparent, accessibly written documentation that describes the way they system uses learner characteritics to adapt instruction to achieve learning outcomes. That is, the design of the tasks needs to be described in terms of *malleable factors* that promote outcomes (Institute for Educational Sciences, 2020). The selection of learning activities itself should increase the likelihood of achieving an outcome. Thereafter, the adaptation of that activity based on information about the student should be based on a theorized moderating factor that further enhances the likelihood that a learner will achieve an outcome. For instance, providing students with opportunities to solve problems is a well-known method of improving their ability to solve future problems (Arroyo et. al, 2011) and adapting the problems posed to the learner so that students are tasked with solving problems involving knowledge they have yet to master speeds their learning and increases what is learned (Kulik & Fletcher, 2016). Indeed, this line of work is most perceptible feature in the initial design of Cognitive Tutors, which were designed according to assumptions of ACT theory (Anderson, 1983), and were refined over a decade of testing to improve ACT-R theory (Anderson et al. 1995, 1997). Such an example illustrates how transparency about the way learning tasks promote learning outcomes and adapting tasks to student characteristics can enhance the benefits to these outcomes.

This kind of transparent logic needs to be extended across PL designs to illustrate how an instructional design approach and adaptation of it achieves its ends. For example, a student's out-of-school interests are often the target of personalization efforts. Designers may explain their PL design by articulating how they use one of two distinct theories of change to achieve a target learning outcome. One designer might provide an opportunity for students to choose and enter topics of interest into a learning task (e.g., nouns into math story problems; Høgheim, & Reber, 2015) if the goal is to promote student motivation for learning (Figure 10; yellow path). A second designer might propose a second theory of change that involves assessing student interests' prior to learning and then tracks students into sets of materials where interest are extensively incorporated into the learning tasks, in order to promote both task interest and achievement (Figure 10, green line; AUTHORS, DATE).

The transparency these example provide would enable educators to make more thoughtful adoptions and implementations of personalized learning that can deliver the specific outcomes they target. The same transparency in design can enable researchers to more systematically investigate individual PL designs and to synthesize research that investigates these malleable factors and their implications for outcomes. This iterative process can then inform future research and design cycles that follow.

**INSERT FIGURE 10 ABOUT HERE**

**A research agenda for personalized learning.** Researchers who aim to contribute to the knowledge base about personalized learning can leverage transparent theories of change and heuristics developed by educational agencies to determine what methods of personalizing learning work to achieve targeted outcomes, for which learners, and under what conditions (What Works Clearinghouse, 2020). Given the diversity of PL designs that have been developed and the complexity of their combination into multi-component personalized learning initiatives in educational practice, this shift will require methods of inquiry spanning classic experimental designs, complex educational research methods, and implementation science approaches.

The methods that designers use to test the functionality, usability, and effects of the products, tools, and features they develop are reasonably well established, and the A-B testing phase aligns to the controlled experiments that educational researchers use to establish causal inferences about learning. More of these studies are needed in order to understand how individual design components within PL initiatives achieve outcomes, and how such designs further need to be crossed to examine how such components interact to moderate independent effects. When additional data about users are available, additional moderating factors can be considered, as can contextual factors related to dosage, timing, and other ways that PL may be adopted in authentic educational settings.

As researchers move from laboratory to applied settings, research designs become more complex, and retaining the ability to make causal inferences would require substantial control of the personalized learning experience. That is, researchers would need to maintain the ability to randomly assign versions of PL that systematically vary in their features to learners and observe their effects. This kind of design is possible in some circumstances when PL involves a single platform that is in sufficient demand that researchers can toggle and study individual features without disrupting users' experience (e.g., ASSISTments Testbed; Ostrow & Heffernan et al. 2016), or when a broad, systematic study is conducted with thousands of users in a form of super-experiment (Stamper et al., 2012). However, these are uncommon opportunities, and the more common district and school-level designs present a pernicious challenge to the conceptualization and study of PL.

When K-12 schools in the U.S. adopt a model of PL, they tend to do so in accordance with a governing educational policy that includes multiple features they must satisfy. By necessity, such programs will often include multiple components in order to satisfy program requirements and address policy goals. Because policies are seldom drafted with explicit theoretical conceptualizations or heavy input from educational researchers, these design and implementation conditions are likely to lead to complex designs that stymie research with confounded designs, affording compulsory involvement but restricting opportunities for a control comparison . The increasing adoption of PL is encouraging, but designs are diverse, implementations are irregular both within and between designs, and studies of school-level designs generally proceed with limited resource and agency. The design of policies and implementations and their study would benefit from ongoing conversation with learning scientists and instructional designers, as well as evaluators who could design innovative, flexible, and systematic studies of implementations and their effects (e.g., McCarthy & Liu, 2020). It may be the case that school implementations of personalized learning need to be considered differently, as they are necessarily multicomponent initiatives that rely on a many-to-many-to-many conceptualization to align to state policies and aim to address many needs of learners and community stakeholders. Should this be the case, a separate education policy agenda will need to emerge, undertaking an implementation science paradigm to evaluate successful components and models (and moderating factors; AUTHORS, DATE).

**Limitations**

Conducting a systematic review of a phenomenon described by numerous definitions and investigated across multiple research communities was a challenge, and the individual differences in publishing conventions, indexing, terminology, and reporting standards imposed limitations on the authoritativeness of this review. We set out to enact a systematic search using indexes that are broadly subscribed in social sciences (i.e., PsychInfo, ERIC, via EBSCOHost) and computer science and engineering communities (i.e., conference proceedings via IEEE Xplorer). This enabled us to confidently search by the keywords and their variants we reported in our methods. However, we quickly found that additional keyword variants would be relevant, but would also add tens of thousands of potential matches, owing to the popularity of "personalization" and "adaptivity" in other fields (e.g., medicine, media). We deemed that screening more than the roughly 1600 manuscripts we considered would be unwieldly and inefficient, given that addition of these broader variants induced even higher false positive rates when we conducted a preliminary screening and found that few met our inclusion criteria. Rather than adopting this method, we undertook a principled method of adding back conferences that were not indexed but were highly relevant venues for the kinds of studies that populated our search (e.g., a conference on User Modeling, Adaptation and Personalization). We did so by using keywords and citation indices to identify the most highly cited relevant conference proceedings on Google Scholar, and thereafter took the advice of expert reviewers to ensure our review was as inclusive as possible of candidate manuscripts to represent contemporary research. When future researchers deem that a critical mass of additional scholarship has accrued that an updated review is warranted, they may consider experimenting further with keyword approaches to capture personalization and adaptivity as they cross with human subjects research on the learning process and its outcomes in order to manage challenges with these many relevant keywords. They may also adopt more complex methods of handling way unindexed conference proceedings are considered in order to increase confidence that relevant research on personalized learning does not go unconsidered.

## Conclusion

Research activity focused on personalized learning is ample, but also arises from multiple communities that do not commonly intersect in their alignment to ideas, nor in their conventions for presentation of findings. Most research into personalization lacked an *a priori* conceptualization that explicitly built upon a stated definition of PL or theory of learning. While evidence suggests that PL designs generally promote the learning outcomes they target, the empirical base is small, diffused, and largely correlational. Further, the evidence base suffers from an inherent disorganization that obscures which PL designs achieve such ends. This arises from the typically complex PL designs that are implemented in practice, wherein many learner characteristics inform many design choices, and which are adopted to promote many outcomes. The state of the research undermines the ability to produce unequivocal evidence of the effects that personalization design choices can have on learner outcomes, and this limits both the development of a cohesive theory of personalized learning and the confidence practitioners can profess when planning a PL implementation. Stronger connections between PL designers and members of the educational research community who are familiar with instructional design principles and theories of cognition, motivation, affect, and sociocultural factors can likely produce designs that yield superior benefits to learners, clearer evidence of the benefits of design choices, and a cohesive theory of personalized learning.

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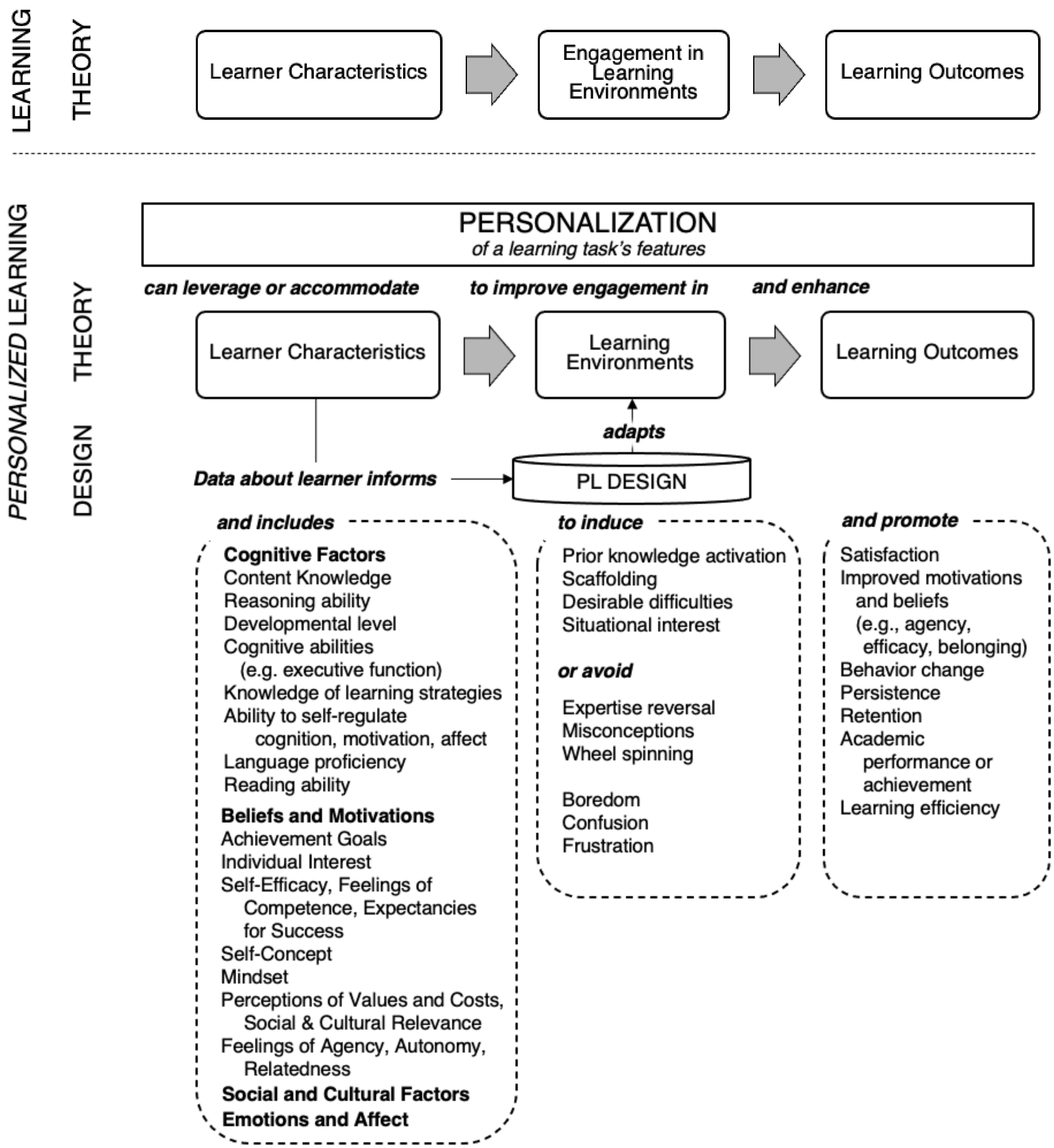
Figure

**Figure 1**

*Instructional Design and Personalized Instructional Design Processes*




*Note*. Instructional Design and Personalized Instructional Design Processes, and a taxonomy of learner characteristics that can be leveraged to inform design choices to achieve learning outcomes; elaborated from Walkington & Bernacki, 2020.

**Figure 2**

*PRISMA model describing systematic review methodology*

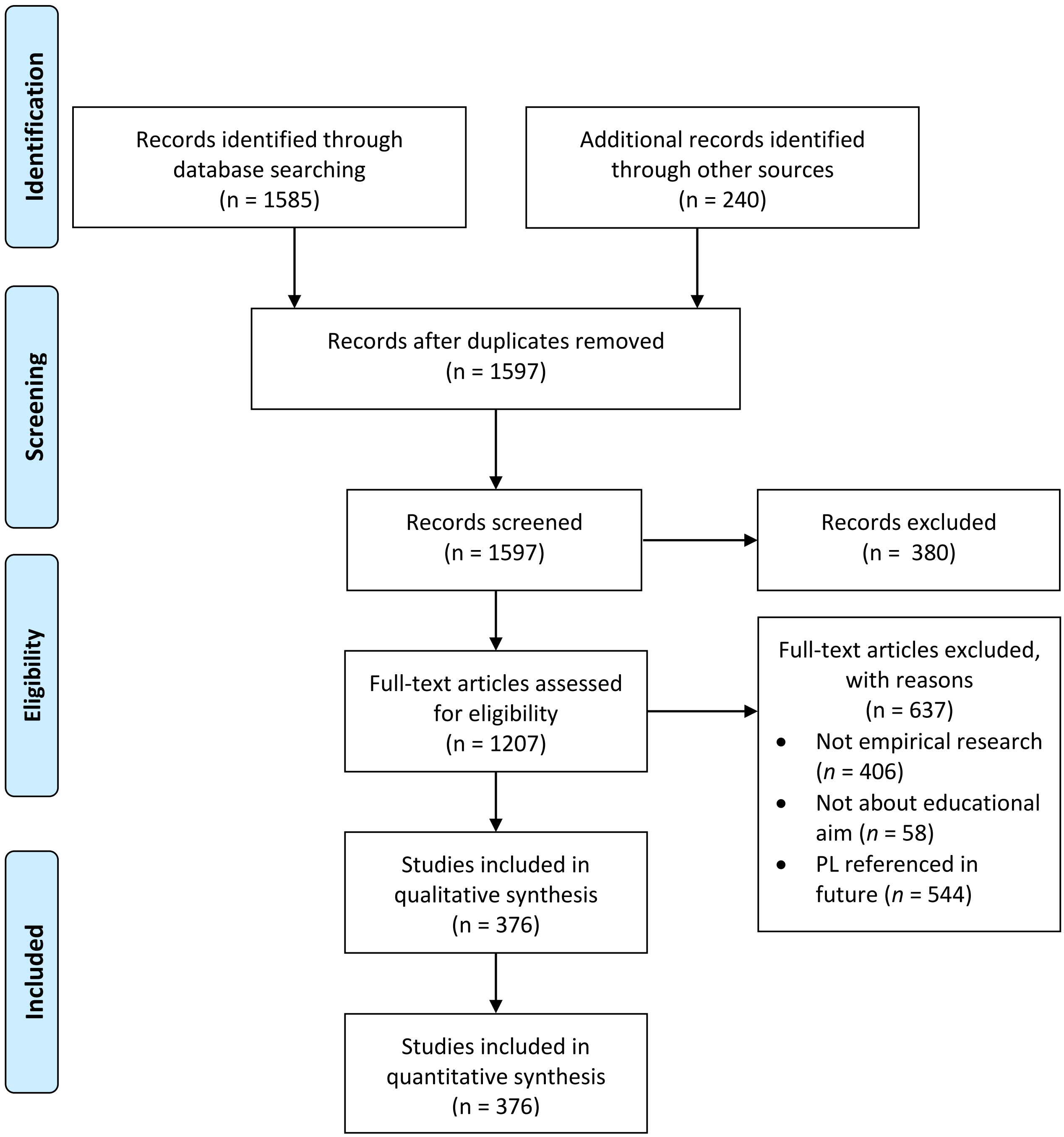
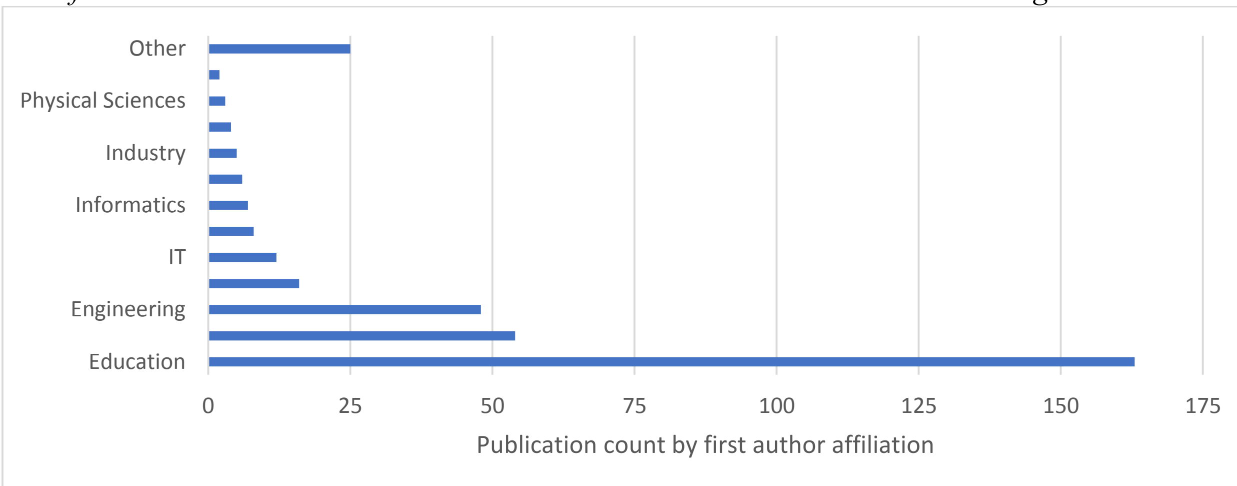


**Figure 3**

*Affiliations of Researchers Who Have Led Published Research on Personalized Learning.*




*Note*. Counts reflect publications based on affiliation of the first author.

**Figure 4**

*Age Groups of Participants in Studies of PL*

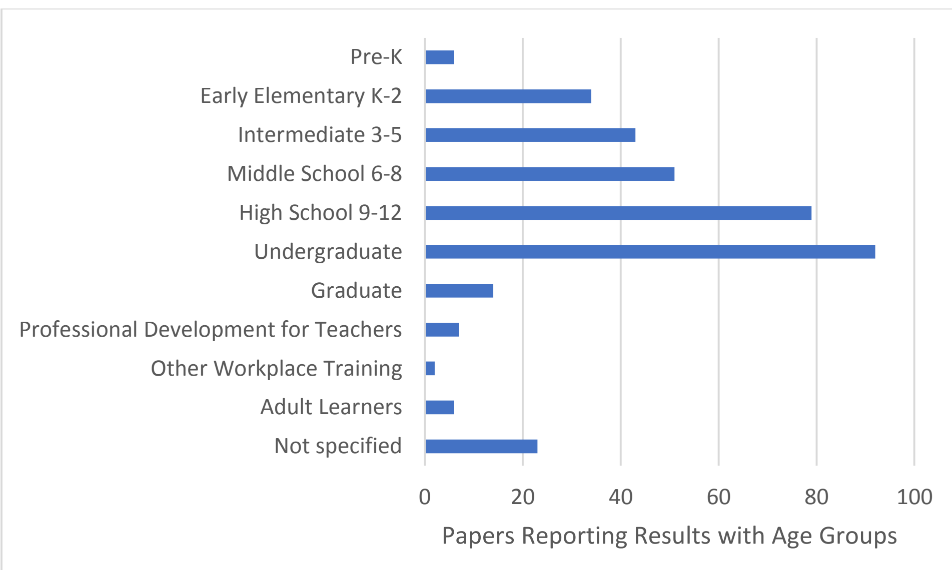


**Figure 5**

*Definitions of PL Word Cloud of All Published Definitions of PL and Specific to Research Led by Education, Engineering, Computer Science, and Other Researchers.*

Total Sample


Education


Engineering


Computer Science


Other

**Figure 6**

*Studies that Investigated Learner Characteristics That Inform PL Design, and the Source of Data Reflecting the Characteristics*

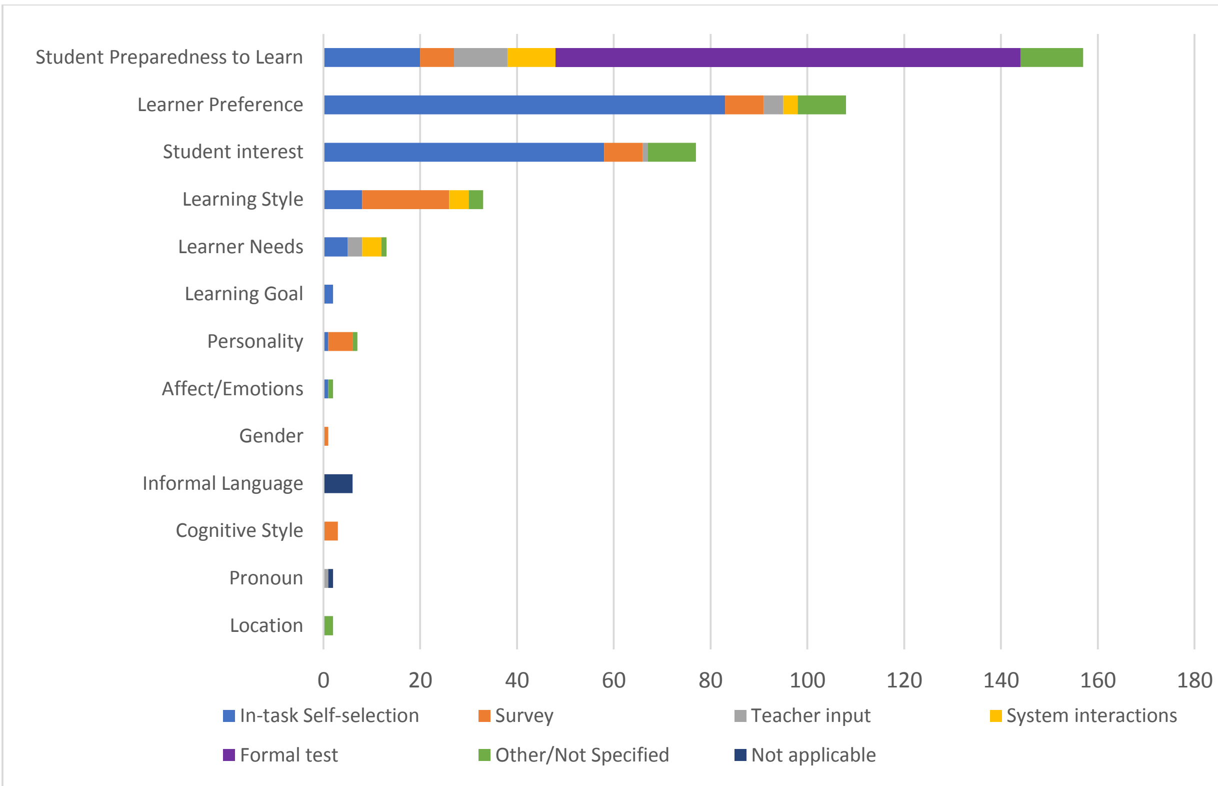



**Figure 7**

*Proportional Focus on PL Research Designs That Accommodated Learner Characteristics by Total Number of Studies (Left) and Percentage (Right).*

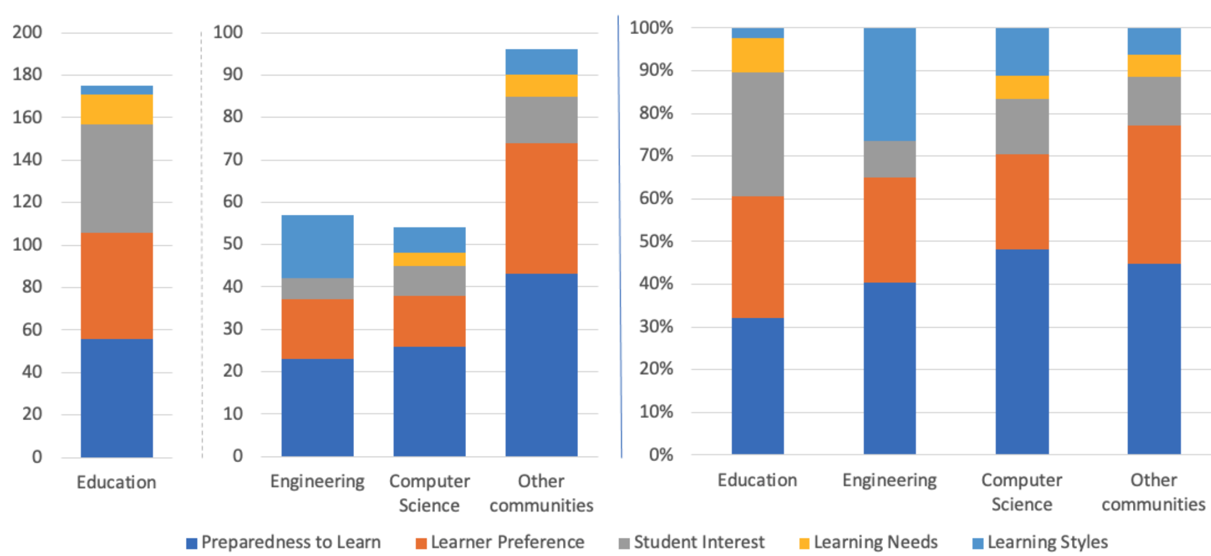
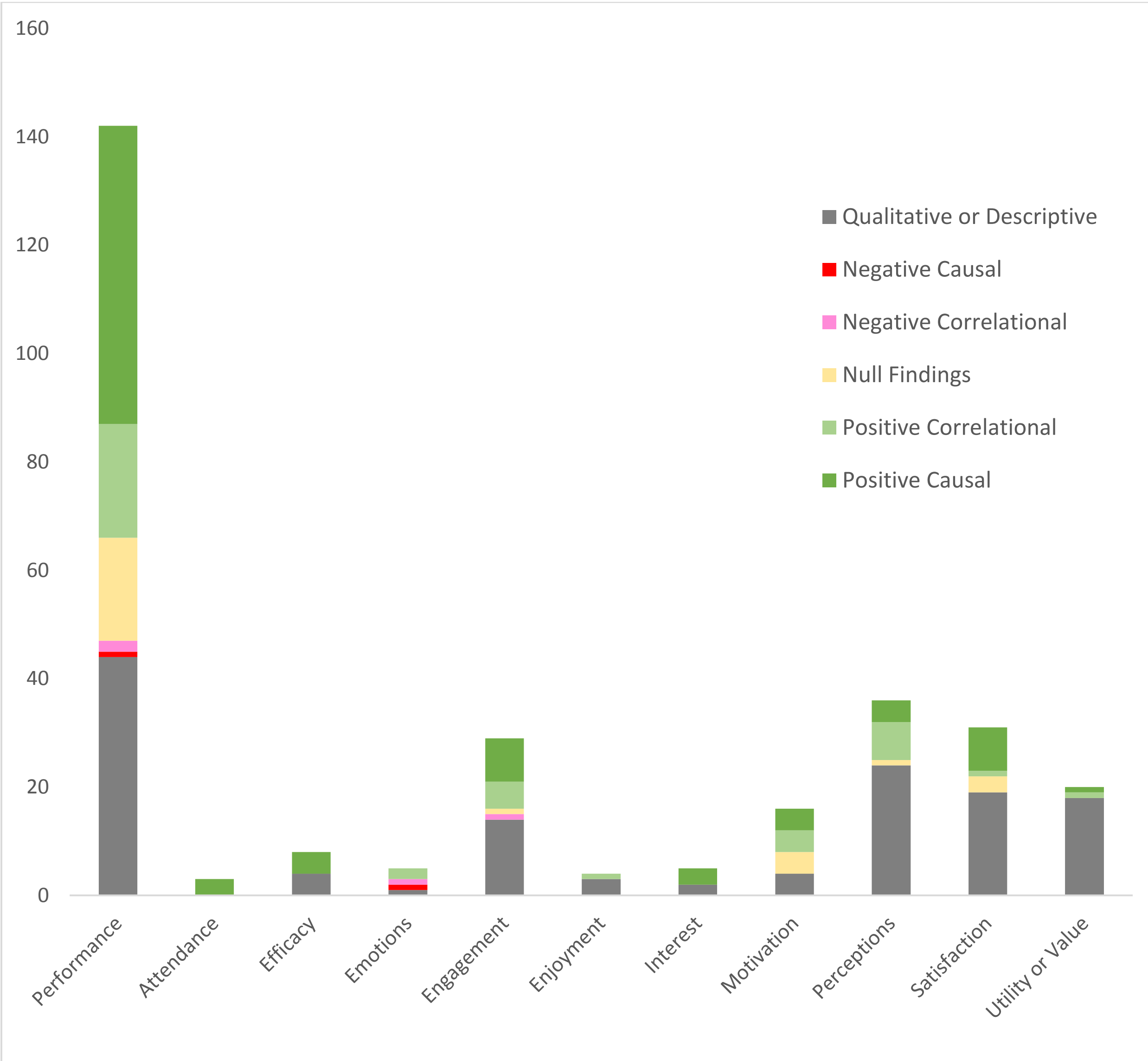


**Figure 8**

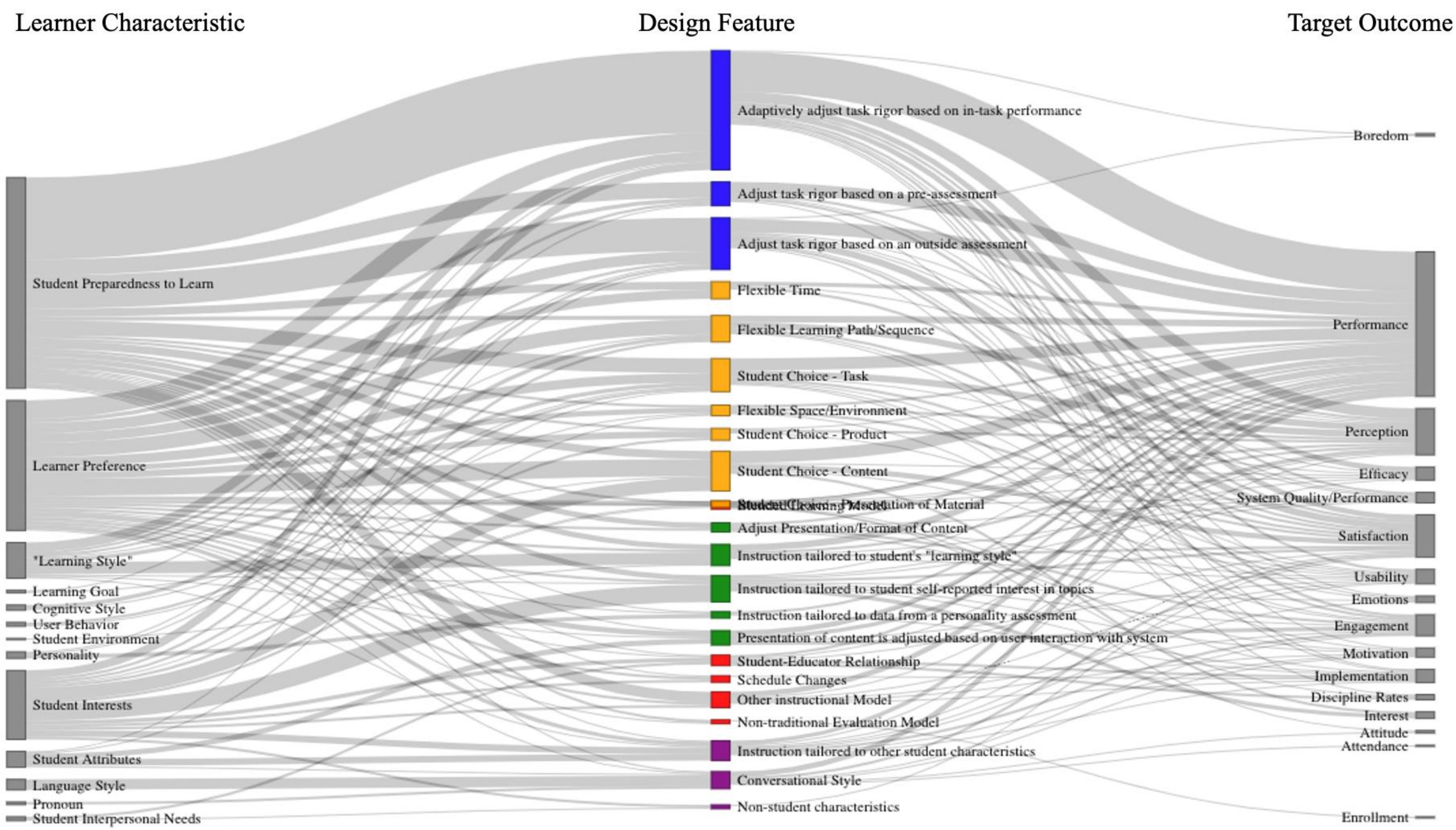
*Dependent Variable PL Is Designed to Affect and Balance of Empirical Evidence of Relationship*




*Note*. Grey bars are include all articles within the corpus evaluated that did not examine an outcome variable as part of the research design.

**Figure 9**

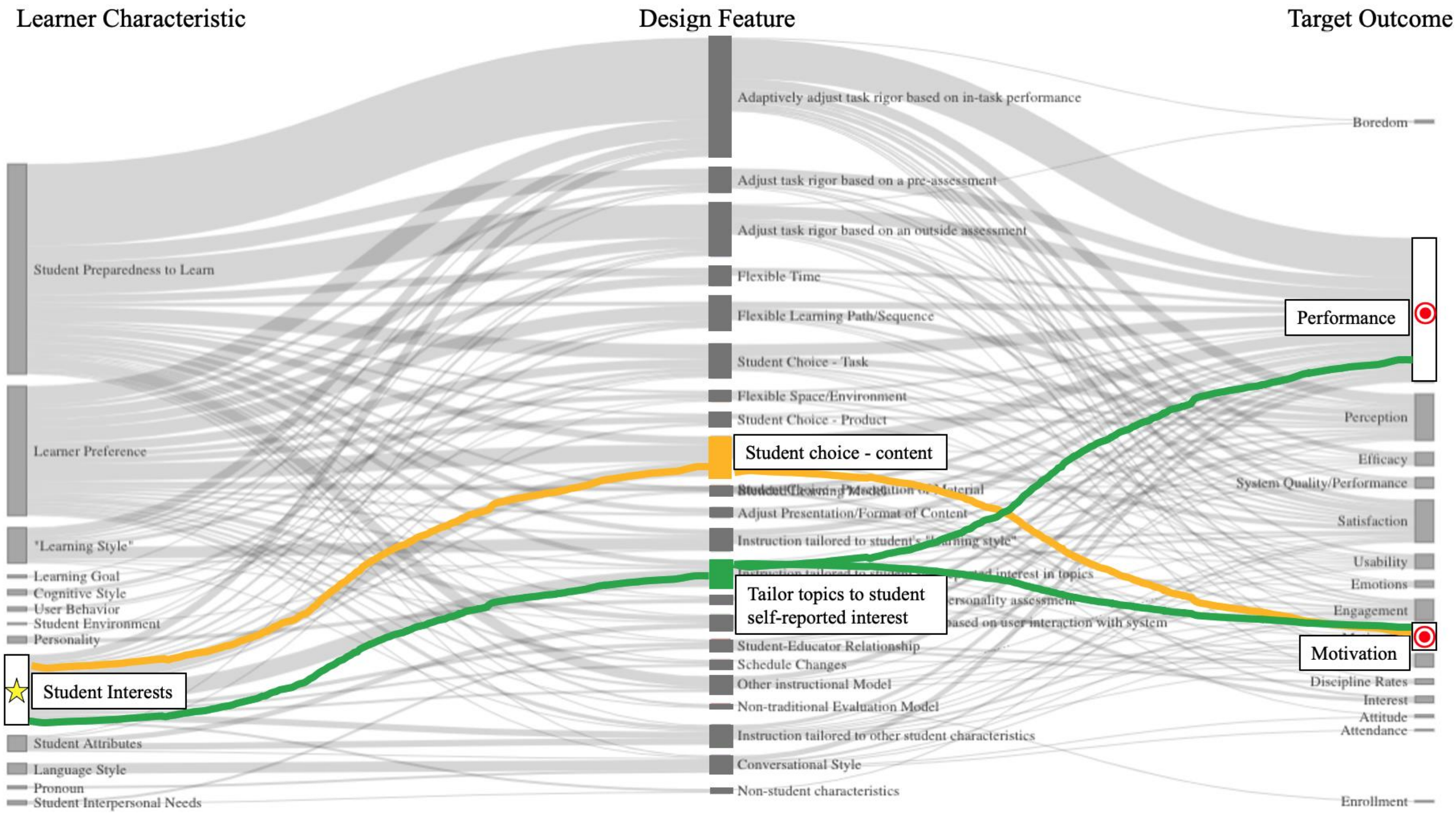
*Relations Among Learner Characteristics and Learner Outcomes Design Elements Personalization Comprises*




*Note*. Frequency of association of characteristics and outcomes (top). Implicit conceptualizations of ways PL design leverage characteristics to achieve outcomes (bottom). Design choices in the middle column indicate designs aligned to personalization based on prior or updated knowledge or skill mastery (blue), students' in-task selections (yellow), and pre-task provision of information (green, purple) or school-wide adjustments to afford ad-hoc PL (red).

**Figure 10**

*Sample Theory of Change: How Context Personalization Designs Accommodate Interests and Promote Performance and Motivation*




*Note*. Colored paths demonstrate context personalization methods (middle column) that accommodate a learner characteristic (left column) theorized to promote improved motivation and performance (right column). The yellow path indicates a design choice previously found to achieve effects on motivation (e.g., Høgheim, & Reber, 2015), and the green paths indicate a design choice that benefitted students' motivation (AUTHORS, DATE 1) and performance (AUTHORS, DATE 1, 2) .

Table

Table 1

*Definitions of Personalized Learning*

| Source | Definition |
|---|---|
| OECD (Jarvela, 2006) | "seven critical dimensions: i) development of key skills which are often domain-specific; ii) levelling the educational playing field through guidance for improvement of students' learning skills and motivation; iii) encouragement of learning through "motivational scaffolding"; iv) collaboration in knowledge-building; v) development of new models of assessment; vi) use of technology as a personal cognitive and social tool; vii) the new role of teachers in better integration of education within the learning society." |
| U.S. Office of Educational Technology (2010) | "instruction that is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners. In an environment that is fully personalized, the learning objectives and content as well as the method and pace may all vary (so personalization encompasses differentiation and individualization)." |
| iNACOL (Patrick et al., 2013) | "Personalized learning is tailoring learning for each student's strengths, needs and interests – including enabling student voice and choice in what, how, when and where they learn – to provide flexibility and supports to ensure mastery of the highest standards possible." |
| Bray & McClaskey (2014) | "In a personalized learning environment, learners actively participate in their learning. They have a voice in what they are learning based on how they learn best. Learners have a choice in how they demonstrate what they know and provide evidence of their learning. In a learner-centered environment, learners own and codesign their learning. The teacher is their guide on their personal journey." |
| Bill & Melinda Gates Foundation (2015) | "In personalized learning settings, teachers assess students' strengths and needs to create learning plans that are aligned with student interests and strong academic standards. This summary provides a brief introduction to the three core elements of personalized learning, along with a snapshot of the key roles that teachers, school systems and leaders, and technology play." |
| U.S. Office of Educational Technology (2016) | "instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner. Learning objectives, instructional approaches, and instructional content (and its sequencing) all may vary based on learner needs. In addition, learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated." |
| Eduvate Rhode Island (2017) | "Personalized learning is a student-centered learning approach where learning experiences are tailored to meet the unique needs and ensure strong growth of each individual student on a real-time basis. Specific approaches of personalized learning are varied." RI adopted 8 themes to inform implementations: individualization, differentiation, standards-aligned, student owned, socially embedded, connected to student interests, in flexible environments, continuous formative assessment. |
| Cuban (2018) | "a revised continuum of classrooms, programs, and schools that encompass distinct ways that "personalized learning" appear in customized lessons as a strategy to achieve short- and long-term goals for schooling the young." |
| SRI Education (2018) | "instruction in which the objectives, pathways, and pace of learning experiences are optimized for each learner's needs, interests, and ongoing performance. … Each of these elements can be assigned to or chosen by students on the basis of measures of their needs, interests, or ongoing academic performance. Personalization thus involves tailoring multiple elements of instruction, stressing the importance of understanding each learner as an individual, and matching learning experiences to his or her needs and interests. Technology is typically a critical tool for enabling these processes. Given this definition, the process of personalized learning can be characterized by a cycle of four processes: (1) engage, (2) measure, (3) interpret, and (4) adapt. |
| Chan Zuckerberg Initiative (2020) | "Providing a truly transformative, personalized learning experience means supporting teachers and students as whole people — supporting not only academic achievement, but also their physical, social, emotional, and identity development." |

Table 2

*Thematic Elements Contained within Definitions of Personalized Learning*

| Source | Learner Characteristics | | | | | Design Components | | | | | | | | Learner Outcomes | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Prior Knowledge / Skill | Interests | Goals | Needs | Preferences | Pace | Approach | Objectives / Content | Sequence | Choice | Scaffolding | Technology | Assessment | Agency | Identity | Motivation | Performance / Skill |
| OECD (2006) | | | | | | | | | | | X | X | X | | | X | X |
| U.S. Office of Educational Technology (2010) | | X | X | X | X | X | X | X | | | | | | | | | |
| iNACOL (2013) | X | X | | X | | | | X | X | X | X | | | X | | | X |
| Bray & McClaskey (2014) | | | | | X | | X | | | X | | | X | X | | | |
| Bill & Melinda Gates Foundation (2015) | X | X | | X | | | | | | | | X | | | | | |
| U.S. Office of Educational Technology (2016) | | X | | X | | X | X | X | X | X | | | | | | | |
| Eduvate Rhode Island (2017) | | X | | X | | | | | | X | | | X | X | | | |
| Cuban (2018) | | | X | | | | | X | | | | | | | | | X |
| SRI Education (2018) | X | X | | X | | X | | X | X | | | X | X | | | | X |
| Chan Zuckerberg Initiative (2020) | | | | X | | | | | | | | | | | X | | X |

Table 3

*Learning Theories Relevant to Personalized Learning Based on Overlapping Focal Learner Characteristics and Related Outcomes*

| **Learning Theory** | **Central Thesis** | **Key Learner Characteristics** | **Focal Outcomes** |
|---|---|---|---|
| *(Meta) Cognitive Theories* | | | |
| Mastery Learning (Block & Burns, 1975) | Learners' current knowledge should inform selection of next tasks; feedback and support should be timely, specific | Prior knowledge and in-task performance | In-task performance, Skill mastery, learning efficiency |
| Expertise Reversal (Kalyuga, 2007) | Support benefits learners with low prior knowledge, undermine those with high | Prior knowledge | In-task performance |
| Working Memory / Cognitive Load (Sweller, 2011) | Capacity is limited; extraneous load should be reduced to afford germane processing | Working memory capacity | attention, performance |
| Metacognition and Self-Regulated Learning (Zimmerman & Schunk, 2011) | Learners bring prior knowledge, skill, goals, and agency; can plan and enact strategies, monitor and adapt learning | Metacognitive knowledge of learning skills, prior knowledge, goals, motivation | goal attainment, motivation, persistence, academic performance |
| *Motivation Theories* | | | |
| Achievement Goals (Elliot, 1999) | Learners may aim to improve /avoid decrease in mastery, performance | Achievement goals | Strategy use, persistence, achievement |
| Interest Development (Hidi & Renninger, 2006) | Learners bring interests that are triggered and maintained by task, mature and change over time | Individual interests | Engagement, persistence, knowledge activation, achievement |
| Self-Efficacy (Bandura, 1986) | The belief that a learner can succeed in learning affects engagement, success | Prior personal, vicarious experiences of success in tasks | Engagement, persistence, achievement |
| Expectancy Value (Eccles & Wigfield, 2020) | Learners appraise tasks to determine expectations, values and costs | Expectancy for success; utility, intrinsic, attainment value; effort, opportunity and psychological cost | Satisfaction, Persistence, academic achievement |
| Self-Determination (Deci & Ryan, 2000) | Learners are autonomous and motivated by choice; they thrive when they feel competent and that they belong | Ability to choose, affinity informing feelings of relatedness, self-efficacy | Satisfaction, persistence, academic achievement |
| *Affect-related Theories* | | | |
| Control Value (Pekrun & Perry, 2014) | Learners' appraisals of control and values arouse achievement emotions during learning, which influence engagement and outcome emotions | Emergent experiences of enjoyment, frustration, boredom during learning | outcome emotions (joy, hope, pride, anxiety, shame, anger) related to success/failure |

Table 4

*Personalization to Learner Characteristics*

| Learner Feature | Description | Percentage by Discipline | | | | |
|---|---|---|---|---|---|---|
| | | Overall | Education | Computer Science | Engineering | Other |
| Student Preparedness to Learn | Prior knowledge of the learner, academic level prior to learning task, Lexile level | 38% | 32% | 46% | 40% | 43% |
| Learner Preference | Learner selections during the learning task (e.g. sequence of activities, types of activities) | 27% | 28% | 22% | 25% | 29% |
| Student Interest | Academic and non-academic interests of students | 18% | 28% | 12% | 9% | 9% |
| Learning Style | Preferential way in which students process, comprehend, and retain information | 5% | 2% | 14% | 26% | 5% |
| Learner Needs | Personal and relational needs of learners | 5% | 7% | 0% | 0% | 4% |
| Informal Language | Conversational style language using first and second person | 2% | 1% | 2% | 4% | 3% |
| Personality | Personality type based on pre-learning task questionnaire | 2% | 0% | 2% | 9% | 2% |
| Cognitive Style | The way individuals think, perceive, and remember information | 1% | 0% | 2% | 0% | 3% |
| Pronoun | Learning tasks use pronouns matching the learners (self-report or teacher-report) | 1% | 1% | 0% | 0% | 0% |
| Location | Physical, geographic location of the learner | 1% | 1% | 2% | 0% | 0% |
| Learning Goal | Specific learning outcome of the learning task | 1% | 0% | 0% | 2% | 1% |
| Affect/Emotions | Mental state associated with thoughts, feelings, behavioral responses, and a degree of pleasure or displeasure | 1% | 0% | 0% | 2% | 2% |

Table 5

*Outcome Variables Targeted by Personalized Learning Designs, by Academic Discipline*

| Outcome | Academic Domain | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Education N = 86 | | Computer Science N = 37 | | Engineering N = 28 | | Other (N= 68) | | Total N = 219 |
| | N | % | N | % | N | % | N | % | N |
| Performance *^ | 41 | 48% | 18 | 49% | 14 | 50% | 25 | 37% | 98 |
| Perception *^ | 15 | 17% | 1 | 3% | 1 | 4% | 13 | 19% | 30 |
| Satisfaction *^ | 6 | 7% | 4 | 11% | 6 | 21% | 12 | 18% | 28 |
| Engagement *^ | 4 | 5% | 2 | 5% | 1 | 4% | 7 | 10% | 14 |
| Efficacy * | 2 | 2% | 5 | 14% | 2 | 7% | 1 | 1% | 10 |
| Motivation * | 6 | 7% | 2 | 5% | 0 | 0% | 1 | 1% | 9 |
| Usability * | 0 | 0% | 3 | 8% | 2 | 7% | 4 | 6% | 9 |
| Implementation | 3 | 3% | 1 | 3% | 0 | 0% | 1 | 1% | 5 |
| Emotions | 1 | 1% | 1 | 3% | 1 | 4% | 2 | 3% | 5 |
| Discipline Rates | 4 | 5% | 0 | 0% | 0 | 0% | 0 | 0% | 4 |
| Interest | 2 | 2% | 0 | 0% | 1 | 4% | 0 | 0% | 3 |
| Enjoyment | 0 | 0% | 0 | 0% | 0 | 0% | 2 | 3% | 2 |
| Attendance | 2 | 2% | 0 | 0% | 0 | 0% | 0 | 0% | 2 |

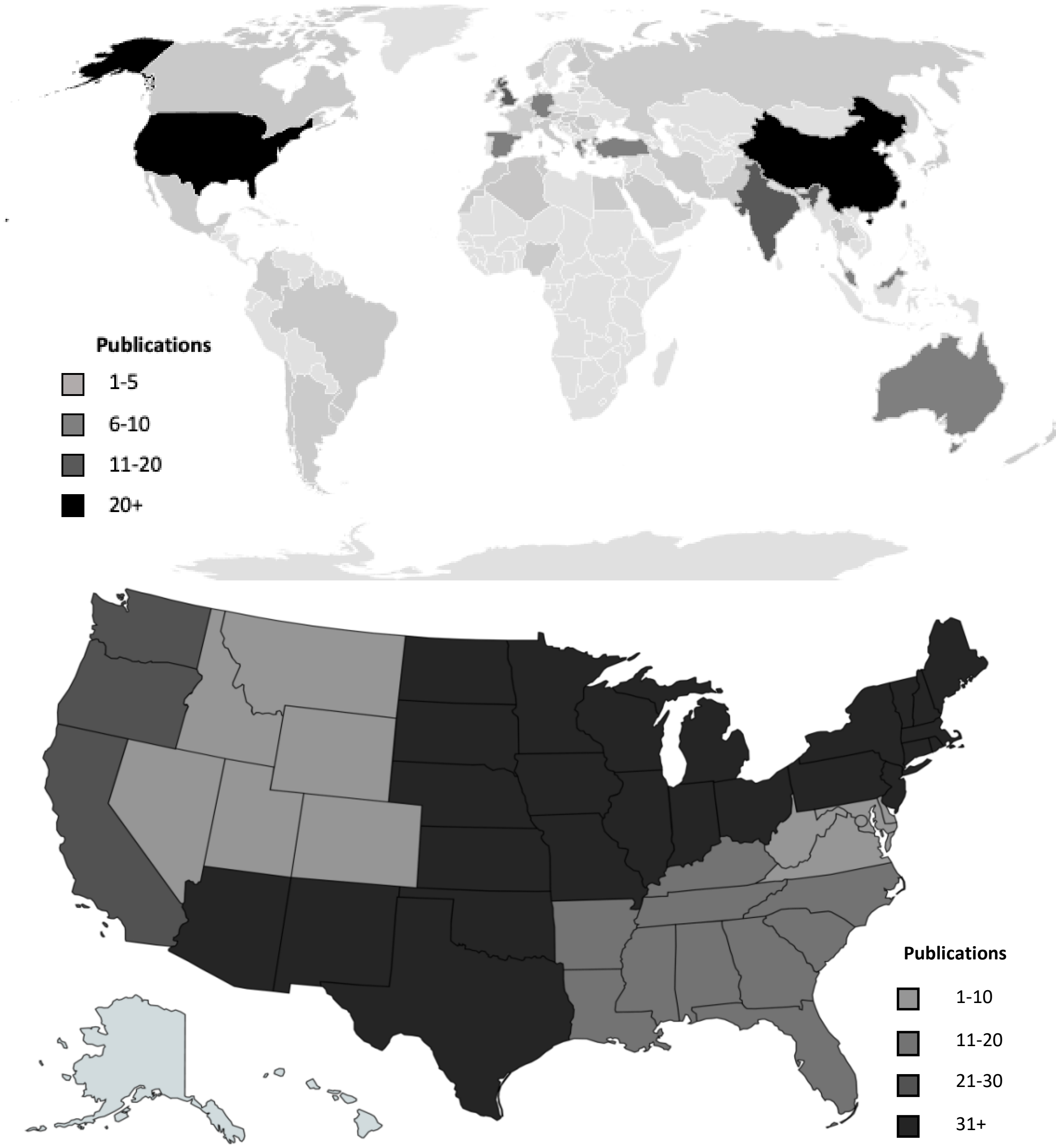
Note. Across all targeted outcome variables, $\chi^2(36) = 55.37$, $p = 0.021$

* - Constrained to the first 7 outcome variables, $\chi^2(18) = 35.70$, $p = 0.008$

^ - Constrained to the first 4, $\chi^2(9) = 16.09$, $p = 0.065$

**Figure S1**

*World and United States (Regional) Choropleth Map of Geographic Locations of Institutional Affiliations of First Authors of Personalized Learning Studies.*




*Note*. Countries with no publication data are shown in light gray. In the US, states with PL policies include Alabama, Alaska, Arizona, Arkansas, California, Colorado, Delaware, Georgia, Illinois, Indiana, Iowa, Maryland, Minnesota, Michigan, Nebraska, New Hampshire, New Jersey, New York, North Carolina, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Utah, Vermont, Washington, West Virginia, Wisconsin, and Wyoming (as of 2018; Zhang et al., 2020).

**Figure S2**

*Publication Venue of Personalized Learning Research*

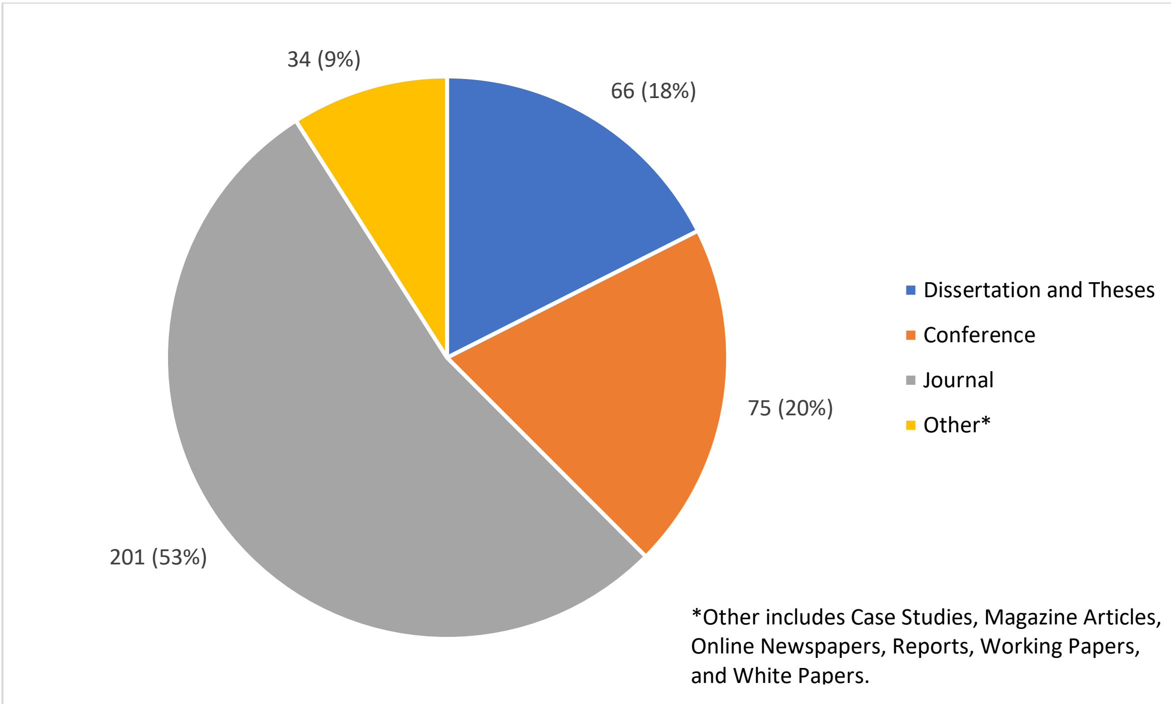


**Figure S3**

*Percentage of Studies Conducted in Digital and Other Contexts, and as Primary or Other Modes of Instruction*

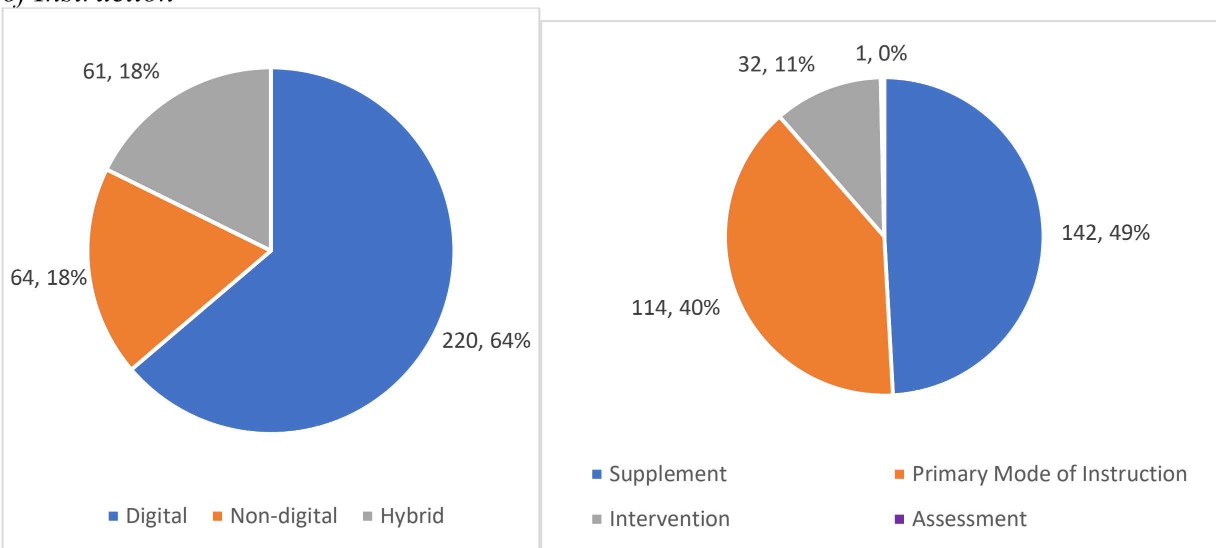



**Figure S4**

*Percentage of Studies Conducted by Academic Domain of the PL Task*

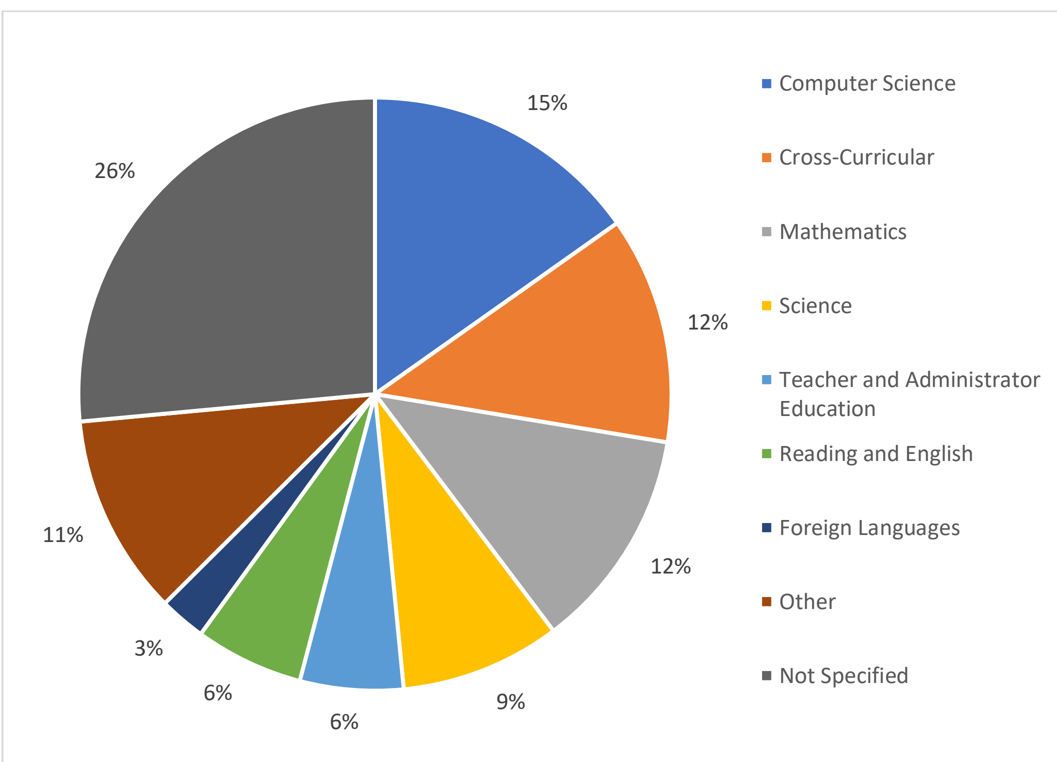


**Figure S5**

*Relations Among Learner Characteristics and Learner Outcomes That Are the Focus of Personalized Learning Initiatives*

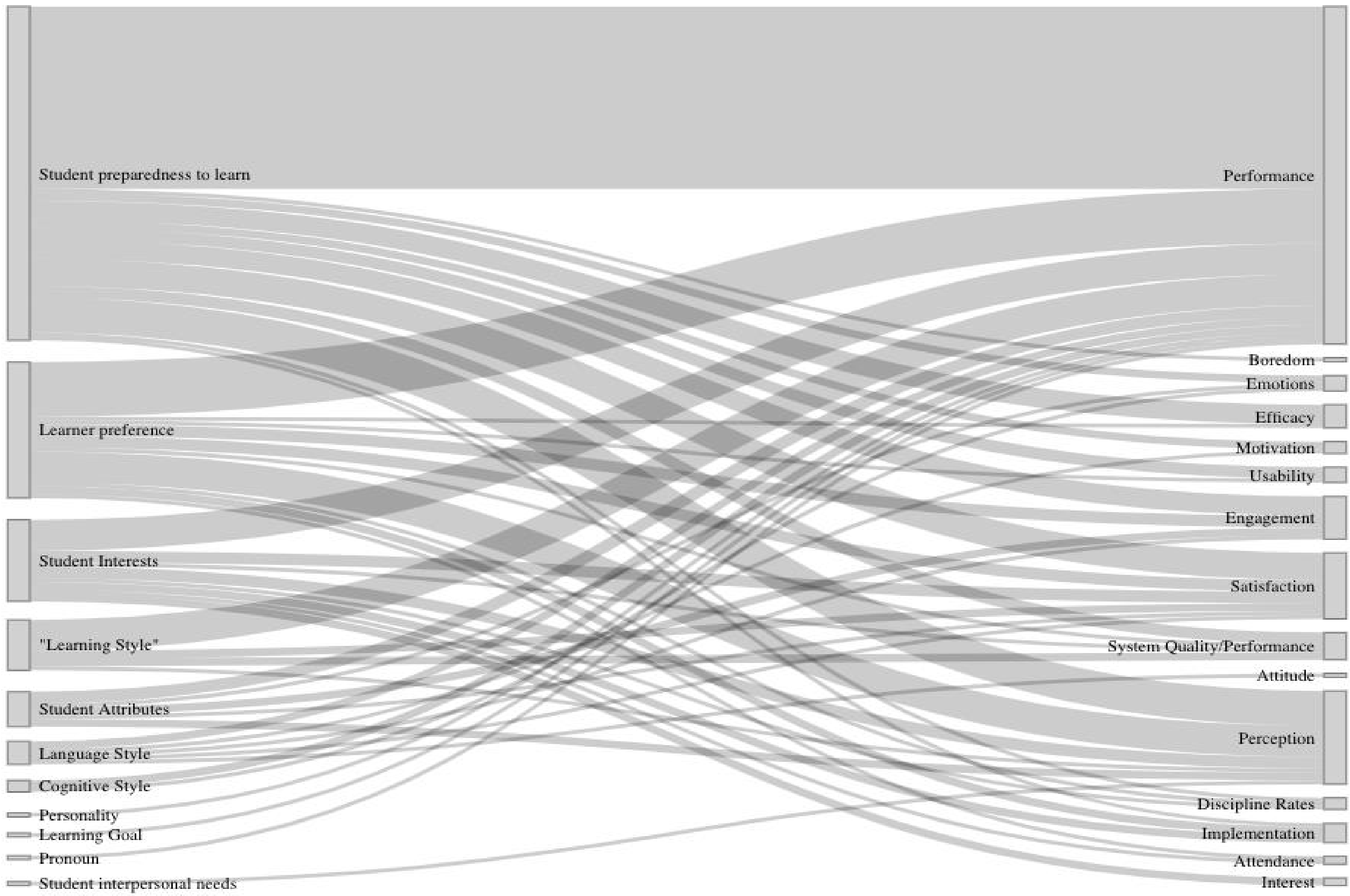


Table S1

*Personalized Learning Studies Screened in and Reviewed, by Publication Venue – Journals*

| Journal | *N* |
|---|---|
| *Computers & Education* | 13 |
| *Interactive Learning Environments* | 8 |
| *Educational Technology & Society* | 8 |
| *Educational Technology Research and Development* | 5 |
| *The Turkish Online Journal of Educational Technology* | 5 |
| *Computers in Human Behavior* | 4 |
| *Informatics in Education* | 4 |
| *Journal of Computer Assisted Learning* | 3 |
| *International Journal of Game-Based Learning* | 3 |
| *International Journal of Distance Education Technologies* | 3 |
| *Research in Middle Level Education* | 3 |
| *International Journal of Web-Based Learning and Teaching Technologies* | 3 |
| *Journal of Educational Psychology* | 3 |
| *IEEE Access* | 3 |
| *Middle Grades Research Journal* | 3 |
| *British Journal of Educational Technology* | 3 |
| *Education and Information Technologies* | 3 |
| *IEEE Transactions on Learning Technologies* | 3 |
| *International Review of Research in Open and Distributed Learning* | 3 |
| *International Journal of Industrial Ergonomics* | 2 |
| *Journal of Online Learning Research* | 2 |
| *Journal of Interactive Learning Research* | 2 |
| *IEEE Transactions on Education* | 2 |
| *International Journal of Artificial Intelligence in Education* | 2 |
| *Journal of Chemical Education* | 2 |
| *Anatomical Sciences Education* | 1 |
| *Educational Action Research* | 1 |
| *Peabody Journal of Education* | 1 |
| *Educational Technology Research & Development* | 1 |
| *Journal of Educational Technology Systems* | 1 |
| *British Journal of Music Education* | 1 |
| *Language Learning & Technology* | 1 |
| *Electronic Journal of e-Learning* | 1 |
| *Teacher Development* | 1 |
| *Emerging Technologies in the Classroom* | 1 |
| *Journal of Educational Multimedia and Hypermedia* | 1 |
| *English Language Teaching* | 1 |
| *Educational Technologies Research and Development* | 1 |
| *European Journal of Psychology of Education* | 1 |
| *Journal on Excellence in College Teaching* | 1 |
| *Frontiers in Psychology* | 1 |

Table S1 (Continued)

*Personalized Learning Studies Screened in and Reviewed, by Publication Venue – Journals*

| Journal | *N* |
|---|---|
| *Mathematical Thinking and Learning* | 1 |
| *IBM Journal of Research & Development* | 1 |
| *ReCALL* | 1 |
| *Campus-Wide Information Systems* | 1 |
| *The Mathematics Teacher* | 1 |
| *IEEE Computational Intelligence Magazine* | 1 |
| *Journal of Educational Change* | 1 |
| *IEEE Journal of Selected Topics in Signal Processing* | 1 |
| *Journal of Educational Research and Practice* | 1 |
| *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje* | 1 |
| *Journal of Experiential Education* | 1 |
| *Educational Horizons* | 1 |
| *Journal of Marketing for Higher Education* | 1 |
| *IEEE Transactions on Emerging Topics in Computing* | 1 |
| *Journal of Social Studies Education Research* | 1 |
| *Computer Assisted Language Learning* | 1 |
| *JSD* | 1 |
| *IEEE TRANSACTIONS ON PROFESSIONAL COMMUNICATION* | 1 |
| *London Review of Education* | 1 |
| *IEEE/CAA JOURNAL OF AUTOMATICA SINICA* | 1 |
| *Middle School Journal* | 1 |
| *Asia Pacific Education Review* | 1 |
| *Principal Leadership* | 1 |
| *Information and Management* | 1 |
| *Education Sciences* | 1 |
| *Computers and Education* | 1 |
| *The Internet and Higher Education* | 1 |
| *Interdisciplinary Journal of e-Skills and Lifelong Learning* | 1 |
| *The Urban Review* | 1 |
| *International Education Studies* | 1 |
| *Journal of Education and Work* | 1 |
| *Educational Policy* | 1 |
| *Journal of Educational Data Mining* | 1 |
| *Biochemistry and Molecular Biology Education* | 1 |
| *British Educational Research Journal* | 1 |
| *CRPE* | 1 |
| *Journal of Educational Technology & Society* | 1 |
| *Educational Psychology in Practice* | 1 |
| *Journal of Educators Online* | 1 |
| *International Journal of Leadership in Education* | 1 |

Table S1 (Continued)

*Personalized Learning Studies Screened in and Reviewed, by Publication Venue – Journals*

| Journal | *N* |
|---|---|
| *Journal of Experimental Education* | 1 |
| *International Journal of Progressive Education* | 1 |
| *Journal of Learning Analytics* | 1 |
| *International Journal of School & Educational Psychology* | 1 |
| *Journal of New Approaches in Educational Research* | 1 |
| *International Journal of STEM Education* | 1 |
| *Journal of School Psychology* | 1 |
| *International Journal of Sustainability in Higher Education* | 1 |
| *Journal of Special Education Technology* | 1 |
| *International Journal of Teaching and Learning in Higher Education* | 1 |
| *Journal on School Educational Technology* | 1 |
| *International Journal of Virtual and Personal Learning Environments* | 1 |
| *Kappan Magazine* | 1 |
| *Democracy and Education* | 1 |
| *Libraries and the Academy* | 1 |
| *International Journal of Web-Based Learning and Teaching Technologies,* | 1 |
| *Malaysian Online Journal of Educational Technology* | 1 |
| *International Journal on E-learning* | 1 |
| *education policy analysis archives* | 1 |
| *US-China Education Review* | 1 |
| *New Horizons in Education* | 1 |
| *User Modeling and User-Adapted Interaction* | 1 |
| *Practical Assessment, Research & Evaluation* | 1 |
| *International Journal of Web-Based Learning and Teaching Technologies* | 1 |
| *Psychology Learning & Teaching* | 1 |
| *Teachers College Record* | 1 |
| *Remedial and Special Education* | 1 |
| *Teachers College Record* | 1 |
| *School Effectiveness and School Improvement: An International Journal of Research, Policy and Practice* | 1 |
| *Technologies for Inclusive Education: Beyond Traditional Integration Approaches* | 1 |
| *Educational Technology and Society* | 1 |
| *The Elementary School Journal* | 1 |
| *Teaching and Teacher Education* | 1 |
| *Journal of Classroom Interaction* | 1 |
| *Technology, Knowledge, and Learning* | 1 |
| *Dyslexia* | 1 |
| *The International Review of Research in Open and Distance Learning* | 1 |
| *Journal of Computer Assisted Living* | 1 |
| *The Learning Organization* | 1 |
| *Journal of Computers in Mathematics and Science Teaching* | 1 |

Table S1 (Continued)

*Personalized Learning Studies Screened in and Reviewed, by Publication Venue – Journals*

| Journal | *N* |
| --- | --- |
| *Education Technology Research and Development* | 1 |
| *Journal of Computing in Higher Education* | 1 |
| *Transactions on Learning Technologies* | 1 |
| *Journal of Early Childhood Literacy* | 1 |
| *Journal of Education and Training Studies* | 1 |
| *ZDM Mathematics Education* | 1 |
| *Journal of Science Teacher Education* | 1 |
| *Journal of Applied Research on Children: Informing Policy for Children at Risk* | 1 |

Table S2

*Personalized Learning Studies Screened in and Reviewed, by Publication Venue*

*– Conference Proceedings*

| Conference Proceeding | N |
|---|---|
| International Conference on Advanced Learning Technologies | 21 |
| IEEE Frontiers in Education Conference | 10 |
| Educational Data Mining Society | 9 |
| User Modeling, Adaptation, and Personalization | 9 |
| International Conference on Computer Science and Education | 6 |
| International Conference on Interactive Collaborative Learning | 5 |
| Intelligent Tutoring Systems | 3 |
| EUROCALL | 2 |
| IEEE Global Engineering Education Conference | 2 |
| International Conference on Technology for Education | 2 |
| IEEE Fifth International Conference on Technology for Education | 1 |
| IEEE International Conference on Advanced Learning Technologies | 1 |
| International Conference of Educational Innovation through Technology | 1 |
| International Conference on Information Technology Based Higher Education and Training | 1 |
| International Conference on Information Technology in Medicine and Education | 1 |
| Learning Analytics and Knowledge Conference | 1 |

Table S3

*Personalized Learning Studies Screened in and Reviewed, by Publication Venue*

*– Unpublished and Unindexed Venues*

| Source | N |
|---|---|
| Dissertation | 66 |
| Center on Reinventing Public Education | 4 |
| International Association for Development of the Information Society | 3 |
| National Center on Scaling Up Effective Schools | 3 |
| Clayton Christensen Institute for Disruptive Innovation | 2 |
| RAND Corporation | 2 |
| Academy for Educational Development | 1 |
| Bill & Melinda Gates Foundation. | 1 |
| British Columbia Teachers' Federation | 1 |
| Editorial Projects in Education | 1 |
| Education Week | 1 |
| North American Chapter of the International Group for the Psychology of Mathematics Education | 1 |
| Project Tomorrow | 1 |
| Research Alliance for New York City Schools | 1 |
| Society for Research on Educational Effectiveness | 1 |
| Stanford Center for Education Policy Analysis | 1 |
| Wisconsin Center for Education Research | 1 |

Table S4

*Personalized Learning Studies Screened in and Reviewed*


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Table S4 (continued)

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