Addressing Learning Variability Through Personalization:

A Brief Summary of the Evidence

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I. Introduction

It is almost a truism that different learners react differently to different teaching methods— sometimes even to the same teaching method at different points in time. If learners are to thrive, it is important to embrace their inherent learning variability (Pane et al., 2015; Corno, 2008). Personalization—the systematic adaptation of instructional parameters to relevant characteristics of a specific learner at a specific point in time (Tetzlaff et al., 2021)—is thus a necessary response to this inherent variability of learning processes.

While learning variability can be addressed at many different levels (individual, classroom, school, society, historical; see Dockterman, 2018), we offer a psychological perspective that is mainly concerned with individual learners and how their variability can be taken into account when designing instruction. This includes considering not just how they differ from other learners at the start of the learning process, but also how their learning prerequisites, needs, and goals change over time. The term learning prerequisites in this case refers broadly to any factor that can affect learning success in general or the success of a specific intervention.

We start by summarizing evidence for the effectiveness of personalization across different contexts and domains. We then outline several challenges that need to be addressed in research in order to better understand the factors that make personalization work. These challenges include methodological difficulties, finding ways to personalize instruction for struggling learners, and potential side effects of personalization. At the end of each section, we briefly outline key questions for future research.

II. What's the evidence base for personalized education?

Human learners differ in a myriad of ways – in their prior knowledge, intelligence, hair color, socioeconomic status, affect, favorite music genre, motivation, working memory capacity, and much more. Personalized learning approaches take these differences into account to optimize the fit of instruction to a specific learner. While the concept of personalized instruction certainly goes back even further, the first psychological perspective on this notion can be traced back to Lev Vygotsky and his theory of the zone of proximal development ((Vygotsky, 1930-1944/1978).). This zone encompasses all tasks or challenges that a learner cannot accomplish without support, but can with support. According to Vygotsky, optimal instruction should always be situated within this zone. The location, size, and malleability of this zone for a given learning objective is defined by the personal characteristics of a specific learner. Not just prior knowledge, but also cognitive characteristics such as intelligence or motivation can influence whether a certain challenge can be met with instructional support. Clearly, these zones are very different for different learners, and instruction that addresses entire groups of learners at the same time runs the risk of being "out-of-zone" for at least some of the target audience. There are, thus, good theoretical reasons supporting personalization, but is there evidence that it actually improves student learning?

Individual tutoring at scale

Initial empirical evidence for the efficacy of personalized education was generated by Bloom's work on individual tutoring. Bloom found that learning gains were up to two standard deviations higher for one-on-one tutoring than for regular instruction (Bloom, 1984). This phenomenon, and the quest to scale up these effects to larger groups of learners, became known as the "2 sigma problem." Although subsequent studies have not been able to replicate the magnitude of this effect, they too have shown that one-on-one instruction is the most effective form of learning (Vanlehn, 2011). The main difference between one-on-one tutoring and conventional instruction is that one-on-one tutors have more *information* and more *opportunities* to adapt their instructional approach to individual learners (Lehman et al., 2008). This applies to the selection of goals and subgoals, the design of instructional units, and assistance during the learning process. Personalization of instruction can thus be conceptualized as scaling up the positive effects of one-on-one tutoring to larger groups of learners without having to provide a tutor for each individual.

This endeavor has proved successful, in principle; across a variety of domains, different approaches to personalizing education have been shown to have positive effects on learning gains. Intelligent tutoring systems, for example, are defined by their assessment of several specific learner characteristics and subsequent adaptation of instruction. They differentiate themselves from regular computer-assisted instruction (CAI) in that they take into account the learning variability of users when providing instruction. Their effectiveness (compared with regular CAI) thus reflects the effectiveness of personalization (Steenbergen-Hu & Cooper, 2014). But in regular classroom instruction, too, formative assessment and internal differentiation can both be viewed as types of personalization, and they have been shown to have positive effects on learning (Allington, 1974; Jung et al., 2018; Slavin, 1987). The common thread running through all of these successful approaches—regardless of context or domain—is that some form of assessment of learner characteristics is used to inform and adapt subsequent instruction.

Failed approaches to personalization

As outlined above, human learners differ in a myriad of ways. However, not all aspects of learning benefit from personalization or are amenable to it. It has become clear that certain approaches are not conducive to increased learning gains. The most prominent example is a focus on learning styles (Truong, 2016; Yang et al., 2013)—the idea that learners fall into one of several distinct and stable categories that moderate the effectiveness of learning depending on the mode of presentation or the organization of the content to be learned. While this approach shows high face validity and quickly found widespread dissemination into practice, current evidence suggests that it is ineffective (Kirschner, 2017; Pashler et al., 2008). Learners may voice preferences concerning the mode of presentation or the organization of learning materials, but they do not show greater learning gains when their preferences are met. Personalization by learning styles is one example of a larger group of personalization attempts that operate by sorting learners into distinct categories that are assumed to be stable over the course of the learning process.

However, personalizing to “static” characteristics of learners appears to be much less effective than adapting to dynamic characteristics, such as prior knowledge (e.g. Rey & Fischer, 2013) or interest (e.g. Walkington, 2013).

Another personalization approach—one that is very prominent in e-learning programs (e.g. McLoughlin and Lee 2009)—puts the focus on learner participation in goal setting and task selection, allowing learners to personalize their own learning paths. This predominantly learner-driven approach is also quite prevalent in some forms of “progressive education” (e.g., Crosby and Fremont 1960). The assumption behind these learner-driven approaches is that learners will generally know what is best for them. Psychological research on metacognition, however, shows that this is not necessarily the case; learners do not always select the most appropriate tasks (Nugteren et al. 2018; Son and Metcalfe 2000). Simply shifting control to the learner is apparently not sufficient for personalizing instruction successfully. Rather, the amount of learner control should be carefully selected in accordance with the relevant learning prerequisites and learning goals (for an exemplary model of such a dynamic allocation of control, see Corbalan et al., 2006).

Key questions for future research

Personalized education can take many different forms, and it can be applied in many different contexts and domains. Can we identify mechanisms that successful personalization approaches have in common?

In a conventional classroom context, adapting instruction to individual students places an additional burden on teachers. How can we support teachers in personalizing their instruction?

II. Methodological challenges in personalization research

One of the key questions in personalization research is whether specific learner characteristics interact with certain instructional parameters to influence learning outcomes. A well-known example of such interaction is the expertise reversal effect: Learners with lower levels of prior knowledge tend to benefit from stronger instructional guidance, whereas the same amount of guidance may be unnecessary or distracting for learners with more prior knowledge (Jiang et al., 2018; Kalyuga, 2007). Similarly, learners with lower general reasoning ability have been found to benefit from stronger teacher guidance, whereas learners with higher general reasoning ability benefit more from stronger self-guidance (Ziegler et al., 2020). Similar interactions have been found between working memory and the effects of conceptual versus fluency activities during instruction (Fuchs et al., 2014).

Multivariate Modelling

What such studies have in common is that they identify a single learner characteristic that might be of great importance for successful learning in the respective learning scenario, and then examine its interactions with various educational interventions. However, multiple learner characteristics can interact with one another, and this interaction may influence the effectiveness of interventions in a different way than the individual characteristics would on their own. In order to model interactions with treatment parameters correctly, these multivariate learner characteristics need to be taken into account.

This phenomenon has been referred to as aptitude complexes (Snow et al., 1987) or trait complexes (Ackerman, 2003). While such multivariate interactions of learner characteristics may occur in various contexts (for some theoretical examples, see Cronbach, 1975) and may have the potential to provide useful insights for individualized instruction, it is difficult to find informative and reliable ways to statistically model such effects. One problem with such models is that interpretation quickly becomes almost impossible, because in an almost endlessly complex manner the interpretation of any effect will always be qualified by another, higher-order effect (Cronbach, 1975). Eventually, there are large numbers of effects that all depend on one another, leaving researchers with a messy picture about what is going on (Bauer & Shanahan, 2007).

Reviewing early research on aptitude-treatment interactions (ATIs), Cronbach (1975) identified potential higher-order interactions as a problem, comparing them to a “hall of mirrors.” This “hall of mirrors” suffers not only from interpretational complexity; other challenges include finding models that can obtain sufficient statistical power to identify effects in such complex data situations (Cronbach, 1975), as well as the nature of interactions that may not always be linear (Bauer & Shanahan, 2007), requiring further steps that complicate the model. Accordingly, although multivariate learning prerequisites represent a topic of great interest to educational researchers, these methodological challenges make it difficult to fully understand such prerequisites and their interactions with educational interventions.

Dynamic modelling

Another commonality of current research on the interaction of learner characteristics with instruction is that those characteristics are usually modeled once, at the beginning of the learning process. Such static conceptualizations necessarily reach their limit as learners and their characteristics change during and in interaction with the learning process. This issue can be addressed by taking a dynamic approach that regularly assesses changes in relevant parameters.

Such a dynamic modelling approach is not new in research on learning. Developmental psychology has been using so-called microgenetic methods (which involve frequent measurements during times of interesting developmental processes) since the 1920s to better understand the development of cognitive competencies in early childhood (Catán 1986). In the field of clinical psychology, there has been a similar push toward dynamic intraindividual patient models (Fisher and Boswell 2016). Recently, we have also seen an increase in studies employing measurement-intensive longitudinal designs, thus recognizing the potential of within-person analyses and dynamic measurement models in educational research (Dumas et al. 2020; Murayama et al. 2017). Even for presumably stable traits such as intelligence, dynamic testing procedures have been shown to produce educationally relevant information beyond that produced by static tests (Resing et al. 2009; Vogelaar et al. 2020).

We argue that a dynamic conceptualization of learners is needed to advance the science of personalized education. This dynamic conceptualization undoubtedly places an additional burden on teachers and other educators. They not only need to regularly assess relevant parameters; they also have to use this information to inform subsequent instructional decisions. Utilizing technology to either assist or replace human teachers in dealing with specific aspects of the educational process would seem to be a necessary requirement for such a dynamic conceptualization.

Key questions for future research

Multiple learner characteristics can interact with one another and influence the learning process, above and beyond the effect of any single characteristic. How can such multivariate learner characteristics and their interaction with instruction be modeled in an efficient way?

A dynamic conceptualization of learners implies a need for personalized interventions to respond to such dynamics. How can the effectiveness of dynamic interventions be assessed?

If learner characteristics are multivariate and dynamic, teachers should take this into account when planning instruction. How can teachers be supported in systematically adapting to dynamic multivariate student characteristics?

III. Learning difficulties and personalization

Learning difficulties are defined as persistent learning-related deficits in one or more domains, including but not limited to reading, writing, and mathematics (Lyon, Flecher & Barnes, 2003). As the label “learning difficulties” comprises a broad range of difficulties and levels of severity (from mere weaknesses to clinical disorders), learning variability and finding ways to address it are of particular importance. In the last 20 years, particularly in the United States, there has been a shift toward a multi-tiered approach to dealing with these difficulties, which is known as response to intervention (RTI). In the RTI approach, learners who are deemed to be at risk are monitored in their response to general education. When they fail to improve, they receive a targeted intervention, and their response is monitored once again. If they again fail to improve, they proceed to the next tier of more intensive interventions. Depending on the system, there are between two and four tiers of increasingly intensive and targeted interventions (Fuchs et al., 2003).

This concept can be traced back to Bloom’s mastery learning approach (Bloom, 1968). In this approach, several small successive learning goals are set and learners progress to the next goal when they have mastered the previous one. This is applicable primarily in settings in which self-paced learning is dominant or when learners are grouped according to their level of mastery (Dockterman, 2018), since each learner is working on a different task, depending on the current goal. As this is not the case in regular classroom instruction, Deno (1990) subsequently expanded on this idea by introducing the concept of formative assessment.

Formative assessment and data-based individualization

Formative assessment (also known as curriculum-based measurement or learning progress assessment) can be seen as an extension of the mastery learning concept aimed at making it possible to use this approach in more traditional grouped instructional settings. The main difference between formative assessment and mastery learning is that in formative assessment, all students are tested on the same overarching learning goal rather than on their current intermediate goal. This allows the teacher to continuously monitor progress on a single scale and to adapt instruction in case of stagnation. In addition, teachers can view the progress of individual students compared with the whole class. Such comparisons enable teachers to use combinations of group- and individually focused instruction, depending on the current needs of the class and each individual student. This approach of teaching to the entire class while simultaneously taking into account individual deviations from the class mean has been termed adaptive teaching (Corno, 2008).

Formative assessment has generally been shown to have positive effects on student learning (Jung et al., 2018; Kingston & Nash, 2011), with some indications that effects are larger for struggling readers. Another striking feature of the studies included in the above-mentioned meta-analyses is the heterogeneity of effect sizes (Kingston & Nash, 2011). This suggests that the positive effects of formative assessment are heavily dependent on moderating factors such as teacher experience or context. It is vitally important to undertake a more detailed investigation into those mediating and moderating mechanisms in order to take full advantage of the potential of formative assessment.

One prominent example of such a moderating factor is the amount and type of support teachers receive when working with the program (Fuchs et al., 2021). Across several studies, the amount of support teachers received in interpreting formative assessment data moderated the effect sizes of the formative assessment intervention (Jung et al., 2018). A knowledge base of interactions between learner characteristic and instructional adaptations is necessary in order to help teachers make the best use of formative assessment data. Such a knowledge base should be carefully assembled with a view to generalizability across domains, cultures, and age groups. There continues to be a stunning lack of research concerning these interactions, with a few notable exceptions. The fact that formative assessment with teacher support produces substantial student learning gains indicates that even without an extensive knowledge base concerning specific instructions, practitioners are able to make informed and effective choices. We believe that such research is still necessary to explain as well as prescribe effective adaptations.

Key questions for future research

Most approaches to dealing with learning difficulties involve remedial courses. How can learners with such difficulties be supported within the regular classroom context?

The effectiveness of formative assessment is heavily dependent on the teachers who implement this approach. How can we support teachers in taking advantage of the full potential of formative assessment data?

v. Too much of a good thing…are there side effects of personalization?

In the previous sections, we have noted that personalized educational technologies should use elaborate learner models to assign “optimal” tasks to learners in a data-driven way. Those personalized systems automate choices and control what learners see on their screens, leaving little choice to the learners themselves. There is strong evidence that most students, and particularly younger children, do not make effective study decisions (e.g., Bjork, Dunloksy, & Kornell, 2013); for example, they may select tasks that are too easy or choose ineffective learning strategies (e.g., rereading, underlining). From this perspective, it may be beneficial to leave little choice to learners. However, there are also potential costs, which we will elaborate on in this section.

Personalization and learner agency

Learner agency refers to learners´ active involvement in educational activities, including their ability to make choices about what, how, and when to learn. In psychology, the term “agency beliefs” refers to an individual’s perceived capacity to produce desired effects through action (Bandura, 2006). This “belief in one’s efficacy” is thought to affect an individual’s goal setting as well as self-regulation and effort while striving to achieve a goal (Bandura, 1989). In a similar vein, self-determination theory posits that greater perceived autonomy is related to increased motivation to learn (Ryan & Deci, 2000). Agency beliefs thus influence how high people set their goals, how they strive to achieve them, and whether they give up easily in the face of difficulties, or instead persist.

To the best of our knowledge, there is no direct empirical evidence on the relationship between personalization and learner’s perceived agency (or lack thereof). However, there is strong evidence that learners prefer learning scenarios that give them choices, and that the corresponding feeling of agency has a beneficial effect on their motivation to learn and retention of facts (e.g., Holden, 1992; Multon, Brown, & Lent, 1991) (Murty et al., 2015; Schneider et al., 2018). It bears mentioning, however, that there is considerably less evidence on the effects of agency on retention of more complex material and over longer periods of time.

Furthermore, the relationship between agency and learning differs between individuals. Student characteristics such as age, knowledge, and cognitive and metacognitive capacities likely all play a role in determining whether greater perceived agency helps or hinders learning. In line with the age-related increase in these capacities during childhood and adolescence, the link between students' agency beliefs and their performance in cognitively challenging tasks has been shown to increase across the elementary and early secondary school years (Chapman et al., 1990).

Personalization and self-regulated learning

Effective self-regulated learning can be conceptualized as a goal-directed process in which learners consciously make decisions that lead toward their learning goals (Azevedo, 2015). Learners with good self-regulated learning skills set goals for their learning and adjust their strategies to attain those goals (Winne, 2017). They also monitor whether their actions support progress toward their learning goals (Azevedo, 2009). Good self-regulation includes choosing to collaborate with others (e.g., study groups, peer learning). Yet, research has consistently indicated that many learners encounter difficulties in self-regulating their learning (Greene & Azevedo, 2010; Järvelä et al., 2013). Consequently, many learners need external support to engage in successful self-regulation.

Similarly, to the best of our knowledge there is no direct empirical evidence on the effects of personalization on the development of self-regulated learning. However, there is strong evidence that self-regulated learning can and must be trained (Dignath et al., 2008). From the perspective of interindividual differences, learners' ability to self-regulate their learning is influenced by learner characteristics such as knowledge and cognitive and metacognitive capacities, and hence there is an age-related increase in the ability to make effective study decisions (Paris & Newman, 1990).

Key questions for future research

When learners are provided with appropriate personalized content, they have fewer opportunities to exert control over their learning. Does this hamper the development of self-regulated learning skills?

Learners have been shown to prefer learning scenarios that give them some choices. Does stronger personalization impede the development of self-efficacy?

When learners are provided with different tasks that are appropriate for their levels of expertise, there are few opportunities for collaboration among learners. Does this hamper the development of social skills (e.g., the ability to collaborate)?

VI. Conclusion

In this brief report, we have reviewed evidence regarding the effectiveness of various approaches to individualization, and we have attempted to identify key questions for future research. There is ample evidence that personalization is a means of dealing with learning variations in a way that allows individuals to thrive. However, not all approaches to personalization are equally effective. Some have not been shown to improve the learning process, while others may even have negative side effects. Furthermore, little is known about how learner characteristics interact in determining the effectiveness of instruction. Because learners differ on multiple dimensions, it seems essential to consider various learner characteristics simultaneously in order to provide truly *personalized* instruction.

Finally, there is much more to the topics of learner variability and personalization than we have been able to cover in this brief paper. While it is important to focus on individual learners and their characteristics, there are also a number of ways in which learning variability can be addressed at the school or even societal level. This include analyzing trends and developments in various aspects of modern life, such as digitalization, and determining how they might be used to improve education.

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