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Chapter 16
Clemson University's Teacher Learning Progression Program: Personalized Advanced Credentials for Teachers

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ABSTRACT

This chapter provides an overview of Clemson University's Teacher Learning Progression program, which offers participating middle school science, technology, engineering, and/or mathematics (STEM) teachers with personalized advanced credentials. In contrast to typical professional development (PD) approaches, this program identifies individualized pathways for PD based on teachers' unique interests and needs and offers PD options through the use of a "recommender system"—a system providing context-specific recommendations to guide teachers toward the identification of preferred PD pathways and content. In this chapter, the authors introduce the program and highlight (1) the data collection and instrumentation needed to make personalized PD recommendations, (2) the recommender system, and (3) the personalized advanced credential options. The authors also discuss lessons learned through initial stages of project implementation and consider future directions for the use of recommender systems to support teacher PD, considering both research and applied implications and settings.

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INTRODUCTION

For more than a decade, teacher and continuing education researchers have recognized that conventional, one-size-fits-all approaches to teacher professional development (PD) accomplish little to improve teachers' professional learning (Caddle et al., 2016; Darling-Hammond et al., 2017). Instead, teacher PD is most effective in improving instructional practices and increasing student achievement when it is aligned to both teacher and school needs and when it is collaboratively grounded in inquiry, reflection, and experimentation (Borko & Livingston, 1989).

As a result, teachers and school leaders have been requesting more personalized PD that is not only sensitive to school needs, but also responsive to individual teachers' interests, skills, career stage, and context (Martinez, 2019)—something consistent with adult learning theory (Trotter, 2006). Until recently, the technological capacity to both design and deliver meaningful, truly personalized PD has been lacking. Ongoing advances in computational techniques associated with recommender systems (Resnick & Varian, 1997), together with expanded but focused learning opportunities, have made personalized PD for teachers a possibility.

Recommender systems are technologies that provide context-specific recommendations to guide users toward the discovery of preferred content or options (Lu et al., 2015). Their utility and versatility have made them popular and essential tools in a variety of environments, including e-commerce and online media (e.g., Netflix, Amazon, YouTube). While the teaching profession and its PD context are different from e-commerce and online media contexts, the technology used in those settings is nonetheless transferrable and can be used to support the identification of personalized recommendations for advanced credentialing based on teachers' interests and needs. Through the project described in this chapter, researchers are developing a hybrid recommendation system that combines an "interests and skills"-based algorithm with a "needs"-based algorithm in order to individualize PD for teachers—to create *personalized advanced credentials for teachers* that meet their unique PD needs.

This chapter provides an overview of Clemson University's Teacher Learning Progression (CU-TLP) program, recently launched with funding support received through the U.S. Department of Education's Supporting Effective Educator Development grant program. CU-TLP provides middle school teachers of science, technology, engineering, and/or mathematics (STEM) with personalized advanced credentials along three graduate credit pathways: (1) Master of Education (M.Ed.) in Teaching and Learning (which has four specialization options); (2) endorsement (which has three options); and/or (3) micro-credentials (which has 21 options across seven topic areas).

The CU-TLP program focuses on supporting teachers by collaboratively uniting STEM teachers and school leaders—especially those working in high-needs, high-poverty schools—with researchers, computer scientists, and PD facilitators in a supportive, technology-enabled system designed to foster personalized professional learning and growth. This approach moves away from the common, one-size-fits-all teacher PD in favor of a more personalized PD system that identifies and delivers recommended PD pathways for teachers based on the needs, interests, abilities, and contexts of teachers and their schools—instead of the common approach of pursuing global PD topics for all teachers within a school over the course of a given year. Through the development and use of a recommender system, CU-TLP provides personalized PD by gathering and analyzing large amounts of data (e.g., student achievement, teacher performance, teacher and school needs) to suggest automated analytical decision-making aid (Fok & Ip, 2006), helping teachers identify the most meaningful PD pathway for them.

In this chapter, the authors first provide the background of the CU-TLP program, briefly highlighting how conventional teacher PD fails to meet the individual teacher's needs and making the case for how personalized advanced credentials for teachers can help address the shortcomings of typical PD approaches. The authors then summarize how a recommender system can be developed and used to identify personalized advanced credentials for teachers. After providing this background, the authors summarize the data collection and instrumentation needed to make personalized PD recommendations; the recommender system; and the personalized advanced credential options available to teachers. Next, some of the early lessons learned through the initial phases of the project are articulated. The authors then conclude the chapter by discussing next steps and considering broader implications for future work in the development and delivery of personalized advanced credentials for teachers.

BACKGROUND

Teachers spend a considerable amount of time receiving PD each year (e.g., Sellen, 2016), but this training is not often successful in bringing about desired changes in teacher practice or enhancing school- and student-level outcomes (Fullan, 2007). Previous research shows that effective teacher PD follows several best practices that encourage buy-in from teachers (Darling-Hammond et al., 2017; see also Sims & Fletcher-Wood, 2021): (1) PD is content and/or standards-focused (i.e., applicable to classroom content and pedagogies); (2) PD engages participants in learning and modeling (i.e., takes an inquiry-based or constructivist approach); (3) PD provides coaching and expert support; and (4) PD is sustained, provided both in-depth and over a meaningful duration. When focused on these evidence-based practices and linked to individual and school needs, PD has the potential to become personalized learning (Wells, 2014).

A five-year study on STEM middle grades teachers showed that highly effective STEM PD can narrow achievement gaps across groups of middle school students while also increasing achievement for all groups. Results further indicated that students in classrooms led by teachers receiving sustained PD support for 1-2 years demonstrated growth on average 6-9 months beyond their peers whose teachers did not receive such PD (Marshall & Alston, 2014; Marshall et al., 2017).

The CU-TLP program moves away from the common one-size-fits-all approach to a personalized PD system by basing recommended pathways on the needs, interests, abilities, and contexts of teachers and schools. Grounded in the National Board for Professional Teaching Standards (NBPTS) Core Propositions, the program provides personalized advanced credentials for teachers to guide teacher growth through an iterative continuous improvement process (Cowan & Goldhaber, 2016; Meyers et al., 2015). Further, the CU-TLP model supports teachers in developing student-centered, inquiry-based learning environments through its content-based PD.

In order to provide iterative, personalized PD pathways to teachers, the CU-TLP team designed and developed a recommender system. As introduced above, recommender systems are technologies that provide context-specific recommendations to guide users toward the discovery of preferred content or options (Lu et al., 2015). In the CU-TLP system, users (i.e., teachers) are matched with items (i.e., personalized advanced credentials recommendations) in order to provide optimal PD pathways for each individual. The CU-TLP recommender system is designed to utilize a hybrid recommendation algorithm, which combines an "interests and skills"-based algorithm with a "needs"-based algorithm. The "interests and skills"-based algorithm augments collaborative filtering—the most prominent type of recommendation algorithm, which allows user recommendations to be created based on users with similar preferences and

behaviors (Schafer et al., 2007)—with work on "self-actualization"—helping users explore and understand their underdeveloped interests (Knijnenburg et al., 2016). The needs-based algorithm implements a retroactive comparison technique to provide developmental pathways based on past successes. This recommender system design is optimal for early model iterations as it allows teachers and PD facilitators to collaboratively improve the system, thus engendering the successes of each cohort participating in the program to inform the next iteration of the recommender system as it develops over time.

The overarching aim of the CU-TLP program—described in detail in the sections that follow—is to create a replicable model that identifies and supports personalized PD pathways, or *personalized advanced credentials for teachers*, designed to improve STEM teacher effectiveness, facilitate teacher retention, and enhance student achievement.

CLEMSON UNIVERSITY'S TEACHER LEARNING PROGRESSION

Program Overview

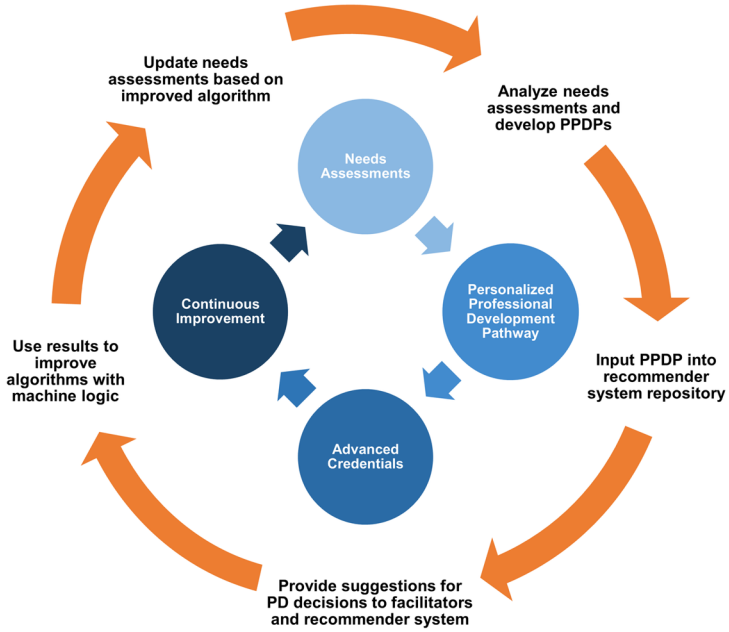
CU-TLP represents a significant advancement from typical or conventional PD approaches (see the model depicted in Figure 1). The inner circles of the model represent the core components and phases of the personalized PD offered through the program. Based on best practices, these core components entail the identification of needs, the specification of personalized PD pathway (PPDP) options, the attainment of personalized advanced credentials, and continuous improvement. The outer arrows represent the iterative process pertaining to the development and use of the recommender system, which will be improved over time by data from the real PD experiences and outcomes of participating teachers.

In the earliest phases of the program, project team members guided the development of personalized advanced credentials pathway options for teachers (as discussed in detail in the sections below). By year three of the project, however, the recommender system will have sufficient data and validated algorithms to assume the main role in determining personalized PD pathway outputs. The researchers anticipate that the resulting collaborative filtering algorithmic recommender system, informed by real PD experiences and outcomes, has the potential to reduce one-size-fits-all learning experiences, save money in low-income schools, improve teacher engagement and outcomes, and be replicable and scalable across multiple settings and disciplines.

Through its initial implementation, CU-TLP is expected to benefit STEM teachers from 19 traditionally underserved local educational agencies (LEAs) in South Carolina, United States, through the provision of personalized, evidence-based PD and enhancement activities. These personalized curricula will improve teachers' classroom-based competencies in STEM, including computer science and socio-emotional skill development; prepare them to deliver rigorous instruction in STEM fields; and support their retention in traditionally underserved schools. For schools, the CU-TLP model provides a more intentional approach for supporting teacher professional growth.

To operationalize the CU-TLP model (Figure 1), CU-TLP personnel are using a methodical four-phase process framework. The framework unites STEM teachers, school leaders, and PD facilitators to provide personalized professional learning and growth to participating STEM teachers. CU-TLP's four-phase process framework is grounded in change-management best practices and includes the following: Phase 1: Pre-Assess; Phase 2: Plan; Phase 3: Do; and Phase 4: Continuous Improvement.

Figure 1. CU-TLP program model



Phase 1: Pre-Assess. Foundational work guides the development of each personalized advanced credentials recommendation for teachers. Generating recommendations for effective personalized advanced credentials for teachers depends on the quality and timeliness of input data, in order to contextualize their PD interests and needs. Initial data collection includes identifying each participating teacher's challenges, strengths, needs, and growth targets. Project team members have utilized needs assessment data to develop and test algorithms that match the interests and needs of teachers with various personalized PD pathways. The needs assessment data collected in Phase 1 provides researchers with local context and enables them to build school- and teacher-level buy-in for CU-TLP pathway offerings.

Phase 2: Plan. In Phase 2, personalized professional development pathway options—that is, personalized advanced credentials for teachers—are developed to provide each participating STEM teacher with a PD pathway. Phase 2 has three critical points fostering school- and teacher-level buy-in. First, recommended pathways are aligned with real needs, as the advanced credential pathways are designed for continuous professional growth and ongoing development of individual STEM teachers. Second, PD facilitators, school leaders, and STEM teachers enter into a partnership—an explicit commitment to pursue competencies outlined in the personalized recommendations. Third, CU-TLP is offering teachers evidence-based PD through advanced credentialing options that equip them to develop and demonstrate mastery of defined instructional competencies and skills. Teachers earn credit for micro-credentials (MCs), endorsements, and/or a degree, with each focusing on developing content knowledge, pedagogical proficiencies, socio-emotional skill development, and/or instructional leadership (e.g., 1-1 mentoring for adult learners, instructional coaching), in accordance with their stated interests and needs. Participating STEM teachers are committed to pursuing at least four targeted MCs, an endorsement, or an M.Ed.

degree pathway. Each MC provides relevant classroom applications and is equivalent to 8-10 contact hours, thus ensuring at least 32-40 contact hours of PD for four MCs.

Phase 3: Do. In this phase, STEM teachers pursue their personalized advanced credentials. Here, the CU-TLP model balances what STEM teachers need and have committed to, via their plans, with what research indicates is likely to result in significant change in teacher effectiveness. CU-TLP's personalized, stackable, advanced credential options are designed to increase teacher knowledge and skills, student achievement, and teacher job satisfaction. As noted, stackable credentials pathways range from individual-level professional growth designed to impact individual classrooms to system-level improvements that seek to effect change through building level leadership. Importantly, the MC, endorsement, and degree options are portable to other districts across the state for recertification credits, state-level licensure endorsements, and salary schedule step increases. These options are also portable to other states with similar requirements for recertification and salary increases. Ultimately, this approach enables talented classroom teachers to build their instructional abilities without having to leave the classroom—benefiting teachers even if they later change schools, districts, or move into other instructional or administrative settings. Depending on the contents of a participating teacher's personalized advanced credentials plan, program personnel expect participants to engage with CU-TLP for at least two years. This timeline supports evidence stating that PD is most effective when sustained over a significant period of time (Supovitz & Turner, 2000).

Phase 4: Continuous Improvement. Learning is a formative process. Part of this continual growth process requires school leaders and STEM teachers to revisit their plans regularly to ensure teachers are advancing toward their targets. Student achievement measures will be gathered during Phases 3 and 4. Many STEM teachers will likely realize they have other areas where further PD is needed based on insights gained and interests identified during program participation.

Having provided an overview of the CU-TLP program, the authors turn now to summarizing the data collection and instrumentation needed to make personalized PD recommendations, create the recommender system, and implement the personalized advanced credential options available to participating STEM teachers.

Project Development and Implementation Timeline

CU-TLP was launched in Fall 2020, with initial funding in place to support the program for three years. By design, participants were intended to be drawn from 19 school districts across the state of South Carolina, with participants from these school districts placed in three distinct cohorts. Fall 2020 was utilized to develop, pilot, and refine the needs assessment and recommender systems (for more detailed information, see the related sections below). Subsequent to the initial development of the needs assessment and recommender system, Cohort 1—composed of teachers from three school districts—began participation in Spring 2021. Cohorts 2 and 3, each composed of teachers from about eight school districts, will begin in Fall 2021 and Spring 2022, respectively (see Table 1).

Profile of CU-TLP Participants

As of the time of this writing, CU-TLP is in the midst of implementation, with Cohort 1 participants in pursuit of their personalized advanced credentials ($N = 97$). Participants are predominantly teachers (86%), but some hold other instructional support (8%; e.g., instructional specialist or coach, media

Table 1. Cohort participation activities and timeline

	Cohort 1	Cohort 2	Cohort 3
Needs Assessment	Spring 2021	Fall 2021	Spring 2022
Pathway Recommendations	Spring 2021	Fall 2021	Spring 2022
Pathway Identification and Commitment	Early Summer 2021	Fall 2021	Spring 2022
Pursuit of Personalized Advanced Credentials	Late Summer 2021 onward	Spring 2022 onward	Summer 2022 onward

specialist) or administrative roles (6%; e.g., assistant principal). Approximately 70% of participants are primarily pursuing an endorsement pathway, while about 16% of participants are primarily pursuing a micro-credential pathway. Finally, about 13% of participants are pursuing a M.Ed. pathway. Across cohorts, an expected 400-500 teachers will engage in the CU-TLP program.

Data Collection and Instrumentation: Identifying Teacher Needs & Interests

In order to identify personalized advanced credentials for teachers, their interests and needs are assessed via an individualized needs assessment (see Appendix). Through this needs assessment, researchers solicit teacher demographic information as well as information about each teacher's current teaching profile (e.g., the grades/subjects/courses taught, self-perceptions of competence, professional goals, areas of strength and areas for improvement); their interests and needs in terms of specific STEM-focused pedagogy and content training; their interests and needs in terms of other training (e.g., social-emotional skill development); and other requisite information in support of their participation in the CU-TLP program (e.g., modality preference, capacity to participate in the program).

The teacher needs assessment provides information to both the recommender system, to identify specific pathway and content recommendations for each individual teacher, and to the PD facilitators, to provide understanding of the learning interests and needs of participating teachers, which is used, in turn, to inform course content.

The Recommender System

Personalized advanced credential options are created for each teacher by a recommender system that considers teachers' individual PD needs and interests. Ultimately, the goal of most recommender systems, and especially the recommender system utilized in CU-TLP, is to two-fold: (1) provide users with items, in this case personalized PD pathway options, that are personally relevant to them while filtering out non-relevant items; and (2) utilize computational technology to rapidly accelerate the rate at which relevant items can be provided to users (Resnick & Varian, 1997; Ricci et al., 2011).

Generally, there are two popular approaches to building recommender systems and accomplishing these two goals: collaborative filtering and content-based filtering (Melville & Sindhwani, 2010). The former, collaborative filtering, often centers on the creation of relationships between different participants to determine item relevancy based on others' choices. Yet, this method generally requires larger populations that represent a large current dataset and are constantly producing new data (i.e., making choices based on recommendations) (Deldjoo et al., 2015). The latter, content-based filtering, utilizes the

content of a user's profile, including their content preferences, to generate recommendations that match the signaled preferences and needs (Lops et al., 2019). An approach similar to content-based filtering was determined to be the most appropriate and relevant method for the initial CU-TLP recommender system due to the target population size and emphasis on the needs assessment data.

The algorithm underlying the CU-TLP recommender system aims to replicate the decision-making process of domain experts (Ricci, 2002). Therefore, the process of building the recommender system started with an extraction and detailing of the logical process that a domain expert would use to filter content based on the data available. In this case, the domain experts consisted of CU-TLP team members familiar with curriculum development and the development of the needs assessment. The knowledge solicited from the expert group was then converted into a logical representation, known as a logic model (Julian, 1997). This model logically connects questions in the needs assessment with corresponding pathways (Razak et al., 2014). Thus, the logic model served as the initial foundation for the algorithmic implementation of the recommender system.

The recommendation platform assigned each pathway an initial value and then scaled that value up or down based on relevant data within a participant's needs assessment, using the logic model as a guideline. The resulting values were then used to rank all possible pathways for a given participant in order to rank an individual's scores and determine which pathway offering(s) would be most appropriate based on the data they provided.

The first iteration of the CU-TLP recommender system platform was heavily biased towards certain pathways, despite not being the best fit for each user. Upon investigation, researchers found that these particular pathways had substantially more factors to consider when making a recommendation, due to the data provided by the first iteration of the needs assessment—meaning there were relatively more opportunities for the system to "flag" or identify a specific pathway as a recommendation and move it up higher in a participant's ranking. To counter this bias, pathways that had fewer considerations in the data were placed higher in the ranking by default, meaning it was much easier for them to end up as a highly recommended item if a participant was interested in them. The resulting algorithm and its generated recommendations were then re-evaluated by the domain experts to confirm the efficacy of the system.

Determining the efficacy of the recommender system was conducted by having the domain experts personally determine recommendations for a random sample of participants, and then comparing their "expert-created recommendations" with recommendations made by the recommender system algorithm. This process is known as a "ground truth comparison" and is essential to ensuring the efficacy of real-world systems (Beel et al., 2013; Binucci et al., 2017). The CU-TLP team used the ground truth comparison to: (1) compare the quality of recommendations created by the system with those made by domain experts; and (2) allow the domain experts to revise their initial logic model with any rules, considerations, or requirements that they may have not considered before collecting data.

Upon completing the ground truth comparison, the researchers found that the computational model and its recommendations were a good fit to the sample provided by the experts; however, small revisions and additions needed to be made to the recommender system algorithm in order to prioritize specific pathways and to consider external requirements limiting the availability of some offerings for certain types of participants (e.g., based on certain eligibility requirements). Upon the implementation of these changes, a second ground truth comparison was conducted on a different random sample. This round confirmed better fit among the recommendations, yet was still compliant with the rules proposed in the first round of ground truth comparison.

The final recommender system provided each participant a maximum of three recommended PD pathways, which included the overall PD pathway, the specific content being recommended in that pathway, and a brief justification for why they were receiving that recommendation. If a participant's data yielded fewer than three strong recommendations (something that could happen as a result of their limited eligibility for certain offerings), then the recommendations were supplemented with a maximum of two alternative options (which did not meet their stated preferences, but did meet their eligibility criteria). The generated list of recommendations—and optional alternative options, where applicable—for the first cohort of participants was fed into an email system via mail merge, which was then used to provide participants with their personalized recommendations.

Personalized Advanced Credentials for Teachers

Personalized recommendations provided to participants included their recommended PD pathway, the specific content being recommended in that pathway, and a brief justification for why they were receiving that recommendation. CU-TLP offers three pathway options to participants, based on their role in the school or district and the subject area they teach. These pathway options are: (1) the micro-credential pathway; (2) the endorsement pathway; or (3) the M.Ed. pathway (see Table 2). All program pathways are offered and facilitated by Clemson University as part of CU-TLP.

Table 2. CU-TLP pathway options and content offerings

	Micro-Credential Pathway	Endorsement Pathway	M.Ed. Pathway
Content Offerings	• Integrating science and engineering practices • Creating engaging math classrooms • Computer science fundamentals • Integrating STEM across the curriculum • Social and emotional learning • Online teaching • STEAM leadership	• STEAM Education • Teacher Leader • Online Teaching	• M.Ed. in Teaching and Learning with specialization in: o STEAM Education o Teacher Leader o Online Teaching o Effective and Reflective Educator

Micro-Credential Pathway

Analysis of the needs assessment data informed the development of the CU-TLP's initial micro-credential (MC) options. Given the explicit focus of the project in terms of supporting STEM teachers, and the data collected through the needs assessment, seven micro-credential topics were established: (1) Integrating science and engineering practices; (2) Creating engaging math classrooms; (3) Computer science fundamentals; (4) Integrating STEM across the curriculum; (5) Social and emotional learning; (6) Online teaching; and (7) STEAM leadership (note: STEAM represents the integration of arts into STEM). A team of expert course developers then created three stand-alone courses per topic, with each course meant to last four weeks and count as one graduate credit hour. MCs can be taken individually from a variety of different topics or sequentially within a topic. As some CU-TLP participants were only interested in taking targeted MCs, the MC pathway was one of the three options available for an individual's personalized recommendation.

Endorsement Pathway

Data from the needs assessment also revealed a high level of interest in endorsements—which reflect an area of specialized training beyond a teacher's certification area—that teachers could add to their teaching certification. In light of this data and the endorsement options available, CU-TLP participants' personalized recommendations could entail suggestions to earn an endorsement in: (1) STEAM Education; (2) Teacher Leader; and (3) Online Teaching. These endorsements, recognized by the South Carolina Department of Education, require a series of four three-credit-hour graduate courses, for a total of 12 hours. Participants were able to be funded for up to 15 credit hours through CU-TLP; as such, many individuals indicated interest in both an endorsement and up to three one-credit-hour MCs.

M.Ed. Pathway

The third pathway option for participants was the M.Ed. in Teaching and Learning. The M.Ed. is a series of ten courses, four of which are the same as the endorsement courses and six of which are general education courses. As participants were able to be funded for up to 15 credit hours, they were informed that they would be responsible for the remaining 15 credit hours in the degree program. Specialization areas for the M.Ed. are: (1) STEAM Education; (2) Teacher Leader; (3) Online Teaching; and (4) Effective and Reflective Educator.

Challenges in Pathway Identification

As participant recruitment began, it quickly became apparent that teachers outside of STEM (such teachers of Social Studies and/or English Language Arts) and staff outside of teaching (such as members of school administration and/or instructional coaches) were also interested in participating in CU-TLP. Yet, one of the primary goals of the program is to support STEM teachers and improve outcomes for students in STEM areas. With these factors in mind, participation criteria were adjusted to include anyone working in a participating school who wanted take part, in the hopes that a collaborative approach to personalized PD across the school would, indeed, help meet the aforementioned goals (Darling-Hammond et al., 2017).

However, difficult decisions still had to be made about eligibility criteria and pathway recommendations, especially for these non-STEM teachers or school leaders. For example, a Social Studies teacher pursuing an M.Ed. with a specialization in Online Teaching would do little to directly impact STEM outcomes for students. On the other hand, an administrator participating in STEAM leadership micro-credentials would seemingly be better equipped to facilitate cross-curricular leadership with a STEM focus in their school. Thus, the following pathway recommendation guidelines were established—which ultimately fed into the eligibility criteria, decision rules, and logic model imposed by the recommender system: (1) STEM teacher recommendations could include all seven MC topics, all three endorsements, and/or all four specializations within the M.Ed.; (2) administration and other support staff recommendations could include all seven MC topics and/or all three endorsements; and (3) non-STEM teacher recommendations could include the STEAM endorsement and/or MCs in integrating STEM across the curriculum. A few examples of personalized recommendations, developed by the recommender system and based on eligibility criteria along with interests and needs articulated through the needs assessment, are provided below.

- **Teacher 1:** A teacher with 13 years teaching experience, a Master's degree, and who teaches mathematics 100% of her time indicated interest in and need for additional STEM training. She also indicated interest in pursuing an endorsement. This teacher was provided a personalized pathway recommendation of a *STEAM Education endorsement*.
- **Teacher 2:** A teacher with two years teaching experience, a Bachelor's degree, and who teaches science 100% of his time indicated interest in and need for additional STEM training. He also indicated an interest in pursuing a Master's degree. This teacher was provided a personalized pathway recommendation of a Master's of Education in Teaching and Learning with a specialization in *STEAM Education.*
- **Teacher 3:** A teacher with seven years teaching experience, a Bachelor's degree, and who teaches social studies with cross-curricular science and math integration was provided a personalized pathway recommendation of micro-credentials in *Integrating STEM Across the Curriculum*.
- **Teacher 4:** An instructional specialist with nine years' teaching experience, a Master's degree plus at least 30 additional credit hours, and who teaches math, science, and other STEM courses and also provides instructional support for other math and science teachers was provided a personalized pathway recommendation of *STEAM Leadership* micro-credentials.

Pathway Recommendations and Participant Commitment Form

The decision rules for different pathways were integrated into the recommender system's logic model. After the generation of final recommendations for all program participants, and in order to communicate recommendations to each participant, an email was sent to each person who completed the needs assessment survey. This email included their personalized recommendations and instructions on how to opt into the program and select a pathway via a program "Commitment Form" (in *Qualtrics*).

LESSONS LEARNED BASED ON INITIAL DEVELOPMENT AND IMPLEMENTATION

Many lessons have been learned during the initial implementation of the CU-TLP program, including during the development and implementation of the needs assessment, the recommender system, and the finalization of pathway recommendations. The primary lessons learned particular to the recommender system—and its novel application within this teacher PD context—is the importance of iterative verification with domain experts (in this case, those who have expertise and knowledge pertaining to teacher PD). While the first iteration of the logic model served as a good starting point for establishing initial recommendations, some "incorrect" recommendations and assumptions existed within the system that resulted in less than optimal draft recommendations for individual teachers. Working with the domain experts to update the logic of the recommender system, using the ground truth comparison approach, improved the recommendations provided by the system. If this iterative process had not been implemented and the recommendations had been issued to participating teachers without first verifying their efficacy, then participants would have received suboptimal recommendations. The iterative human-centered verification process demonstrated great utility and will be implemented for future iterations of the recommender system.

Additional iterations to the recommender system will also allow the recommendations provided to be more sensitive to school-level needs, e.g., through the use of a school-level needs assessment that complements the information provided by individual teachers. For example, a school-level needs assessment could provide the recommender system with data that accounts for the interests and needs of a collective of STEM teachers (e.g., based on STEM teachers' competence within an entire school), along with the district's or school's professional development learning needs and priorities for STEM teachers. Adjustments to the needs assessment process will be carried out as the program moves into Phase 4: Continuous Improvement.

Along the same lines, the teacher needs assessment itself went through a process of iteration, and it will continue to need further iteration and refinement as part of the Phase 4: Continuous Improvement. While the initial teacher needs assessment was sufficient to provide information to the recommender system and to the PD facilitators, capturing more nuanced information along some of its dimensions will help further enhance the quality of the recommender system's output as well as provide greater clarity about the PD content participating teachers need to receive. For example, if participating individuals already have advanced degrees, greater specificity about what degrees are held, in particular, will help the recommender system to be enhanced to provide more targeted recommendations.

FUTURE DIRECTIONS

CU-TLP will provide opportunities to advance theory, knowledge, and educational practice. Replication in part or in whole (e.g., needs assessments, recommender system algorithm, personalized advanced credentials for teachers) provides enormous opportunity to advance the field in terms of developing, leading, and facilitating personalized PD for teachers.

Advancing Theory and Knowledge

Collectively, the CU-TLP program represents a unique approach to how personalized teacher PD is conceptualized and facilitated. The holistic model focuses on teacher and school needs, utilizes a data- and algorithm-driven recommender system to generate personalized advanced credentials for teachers, provides options for various advanced credential pathways, and is designed and refined based on needs and best-practice for PD. Over time, CU-TLP will allow us to better understand the relationship between personalized PD, teacher learning, teacher effectiveness, and student achievement for STEM teachers and their students.

Education research has focused on personalized, differentiated instruction for students for many years (Tomlinson, 2014), but less attention has been directed toward personalized PD for teachers, who are quite obviously adult learners. Aided by a data- and algorithm-driven recommender system, the results of CU-TLP will generate insights to inform ongoing and future research in this area. The authors anticipate that this work will help advance what are seen as best practices in PD. Advancements may include understanding how the amount of PD experiences, the duration, the order of coursework, and the topics of PD affect teaching effectiveness and student achievement. Moreover, in school learning environments altered by COVID-19 (and continued uncertainty in the aftermath of the global pandemic), the CU-TLP team is positioned to identify, track, and respond to shifts in demands expressed by teachers as

they deal with new challenges like shifts to virtual learning and/or the delivery of online synchronous, asynchronous, or hybrid instruction.

Advancing Educational Practice

Clemson University's accredited teacher preparation programs have and continue to demonstrate great success with pre-service teachers. For the past three years, its teacher preparation programs have shown a 99.2% pass rate on PRAXIS II. To further advance the quality of teacher education, the College of Education began the state's first Teacher Residency program four years ago. This bachelor's-to-master's program includes an entire year of teacher residency during year five. The program has experienced dramatic growth (with 72 new students entering Fall 2020). The additional preparation builds confidence and advances capabilities which allows greater success in more challenging settings—thus promoting greater retention.

The authors recognize, as part of their university's land grant mission, their ongoing responsibilities to support teachers, school districts, and communities, and to advance educational practice and address challenges faced by those they serve. The College of Education recently began a college-led induction program (Perfecting Your Roar) to provide additional supports for all state teachers during their first two years. It has also now developed articulation agreements with high schools and technical colleges (Expressway to Tigertown) to assist in creating new pathways for prospective teachers. Additionally, the College recently launched the Center for the Recruitment and Retention of Diverse Educators, focused on establishing partnerships with school districts throughout the state to identify and address barriers to teacher recruitment and retention. CU-TLP, with its focus on personalized professional development for in-service middle school STEM teachers at various career stages, complements these and other initiatives. It is also envisioned to be scalable to other districts, grade levels, and content areas, and also replicable in other state contexts.

Continuing the Development of the Recommender System

The current iteration of the recommender system only considers the data provided by users through their individual needs assessments. Due to the program's emphasis on personalized pathway recommendations, this data was deemed to be the most appropriate for the CU-TLP's foundational recommender system. The next step for expanding the recommendation process involves supplementing users' needs assessment data with data provided by schools via school-level needs assessments. This will allow the recommender system to reconcile participants' preferences with the strategic considerations and needs of their schools. The first set of recommendations puts user needs as the foundational data source of the recommender logic; with this foundational logic in place, the researchers look toward integrating and validating changes that support the inclusion of school-level needs.

Advancing Recommender System Research

Generally speaking, research initiatives regarding the recommender system in this project are predominantly focused on determining the optimal method of presenting recommendations to users. Since the goal of the CU-TLP program is to provide teachers and other participants with consistent and high-quality recommendations in order to improve teacher effectiveness, teacher retention, and student achievement,

the researchers cannot manipulate (e.g., for research purposes) the recommendations provided to program participants. Thus, a more fruitful direction for future CU-TLP recommender system research is to continuously utilize high-quality recommendations while changing the way those recommendations are communicated to users. Research in recommender systems has shown the impact of the interface presenting recommendations to users; allowing users to interact with recommendations often substantially outweighs the effect of the underlying algorithm of system logic (Knijnenburg, Bostandjiev et al., 2012).

As such, research in this area may center on providing intuitive visualizations of the recommended pathways along with studying if and how methods of interacting with these recommended pathways may increase users' investment or commitment to the recommendations they receive. Ultimately, these research initiatives will be carried out with the goal of improving the user experience (Knijnenburg, Willemsen, et al., 2012), specifically in terms of receiving and accepting the recommendations created by the CU-TLP recommender system.

CONCLUSION

In this chapter, the authors provided an overview of Clemson University's TLP program, which offers participating middle school STEM teachers with personalized advanced credentials. The program has been designed to offer PD pathway options to teachers that are sensitive to their individual PD interests and needs—an approach that runs in stark contrast to typical one-size-fits-all PD approaches. Instead, CU-TLP identifies individualized pathways for PD based on each individual teacher's interests and needs, and then offers PD options through the use of a recommender system. The CU-TLP program is thus creating a replicable PD model offering personalized advanced credentials for teachers in order to improve STEM teacher effectiveness, facilitate teacher retention, and enhance student achievement.

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KEY TERMS AND DEFINITIONS

Endorsement: An "add-on" to a teacher's certification indicating completion of training in a specialized area.

Micro-Credential: Topical-focused professional learning modules that provide a means for STEM teachers to improve their content knowledge, instructional practice, and/or socio-emotional skill development in targeted ways.

Needs Assessment: The process of collecting (e.g., via a survey, interviews, or some other means) and analyzing data in order to identify specific content area or pedagogical training teachers need to enhance their instructional effectiveness.

Personalized Learning: An approach to organizing teaching and/or learning activities to meet each individual's unique learning interests and needs.

Professional Development: A general term for content- and pedagogy-related training and/or development opportunities provided to teachers, intended to enhance their knowledge, skills, expertise, and teaching practice.

Recommender System: An algorithm-driven, technology-based system providing context-specific recommendations to guide teachers toward the identification of preferred PD pathways and content.

STEAM: A transdisciplinary approach for engaging learners to solve real-world problems, regularly inclusive of the integration of arts into STEM areas.

STEM: The disciplinary and professional practice areas related to science, technology, engineering, and mathematics.

APPENDIX

Clemson University's Teacher Learning Progression Program: Personalized Advanced Credentials for Teachers

Teacher Needs Assessment

Demographic Information

1. First Name: (text entry)
2. Last Name: (text entry)
3. Email: (text entry)
4. District: (drop down)
5. School: (select all that apply)
6. Current role: (select all that apply)
7. Number of years teaching: (drop-down)
8. Highest level education attained: (Select one)
    a. Bachelor's, Bachelor's +18, Master's, Master's +30, Doctorate
9. What are your current teaching certification fields and endorsements? (text entry)
10. Gender: M / F (Select one)
11. Hispanic: Y / N (Select one)
12. With which racial category do you identify? (Select all that apply)
    a. Asian or Asian American
    b. Black or African American
    c. Latina/Latino/Latinx
    d. White
    e. Two or more races
    f. Other (write in)

Current Teaching Profile

13. What grade(s) do you currently teach? (Select all that apply)
    a. 5/6/7/8
14. What subject area(s) do you currently teach? (Select all that apply)
    a. Mathematics/Science/Computer science/Other STEM
15. What classes do you currently teach? (text box)
16. Percentage time you currently spend teaching
    a. math classes (slider)
    b. science classes (slider)
    c. computer science classes (slider)
    d. other STEM classes (slider)
17. Rate yourself in each of the competencies listed below. (Select one) Scale: I need a lot of improvement, I need a little improvement, I can do this well, I can teach others how to do this

   a. Planning, Developing, and Using Assessments
   b. Establishing and Maintaining High Expectations for Learners
   c. Using Instructional Strategies to Facilitate Learning
   d. Providing Content for Learners
   e. Monitoring and Enhancing Learning
   f. Maintaining an Environment that Promotes Learning
   g. Managing the Classroom
18. What are your professional goals for the current year? For example, what is listed in your current Professional Growth and Development and/or Goals Based Evaluation Plan for this year? (text entry)
19. What additional information would you like to share about your strengths as a teacher? (text entry)
20. What additional information would you like to share about the areas where you need to improve most as a teacher? (text entry)

Personalized Advanced Credentials for Teachers – Interests & Needs

Content & Pedagogical Training

21. You indicated you spend some time teaching math classes. (Conditional on response to 16a; 21 a-d only shown if 16a slider response is >= 1%)
    a. How competent are you at teaching these classes? (Select one)
       i. I need a lot of improvement, I need a little improvement, I can do this well, I can teach others how to do this
    b. I need training in math *content* during the next year (Select one)
       i. Strongly disagree, disagree, agree, strongly agree
    c. I need training in math *pedagogy* during the next year (Select one)
       i. Strongly disagree, disagree, agree, strongly agree
    d. How much would you like to receive training in this area during the next year? (Select one)
       i. Not at all, neutral, somewhat, very much
22. You indicated you spend none of your time teaching math classes. How much would you like to receive training in this area during the next year? (Select one) (Conditional on response to 16a; 22 only shown if 16a slider response is = 0%)
    a. Not at all, neutral, somewhat, very much
23. You indicated you spend some time teaching science classes. (Conditional on response to 16b; 23 a-d only shown if 16b slider response is >= 1%)
    a. How competent are you at teaching these classes? (Select one)
       i. I need a lot of improvement, I need a little improvement, I can do this well, I can teach others how to do this
    b. I need training in science *content* during the next year (Select one)
       i. Strongly disagree, disagree, agree, strongly agree
    c. I need training in science *pedagogy* during the next year (Select one)
       i. Strongly disagree, disagree, agree, strongly agree
    d. How much would you like to receive training in this area during the next year? (Select one)

    i. Not at all, neutral, somewhat, very much

24. You indicated you spend none of your time teaching science classes. How much would you like to receive training in this area during the next year? (Select one) (Conditional on response to 16b; 24 only shown if 16b slider response is = 0%)
    a. Not at all, neutral, somewhat, very much
25. You indicated you spend some time teaching computer science classes. (Conditional on response to 16c; 25 a-d only shown if 16c slider response is >= 1%)
    a. How competent are you at teaching these classes? (Select one)
        i. I need a lot of improvement, I need a little improvement, I can do this well, I can teach others how to do this
    b. I need training in computer science *content* during the next year (Select one)
        i. Strongly disagree, disagree, agree, strongly agree
    c. I need training in computer science *pedagogy* during the next year (Select one)
        i. Strongly disagree, disagree, agree, strongly agree
    d. How much would you like to receive training in this area during the next year? (Select one)
        i. Not at all, neutral, somewhat, very much
26. You indicated you spend none of your time teaching computer science classes. How much would you like to receive training in this area during the next year? (Select one) (Conditional on response to 16c; 26 only shown if 16c slider response is = 0%)
    a. Not at all, neutral, somewhat, very much
27. You indicated you spend some time teaching other STEM classes. (Conditional on response to 16d; 27 a-d only shown if 16d slider response is >= 1%)
    a. How competent are you at teaching these classes? (Select one)
        i. I need a lot of improvement, I need a little improvement, I can do this well, I can teach others how to do this
    b. I need training in other STEM *content* during the next year (Select one)
        i. Strongly disagree, disagree, agree, strongly agree
    c. I need training in other STEM *pedagogy* during the next year (Select one)
        i. Strongly disagree, disagree, agree, strongly agree
    d. How much would you like to receive training in this area during the next year? (Select one)
        i. Not at all, neutral, somewhat, very much
28. You indicated you spend none of your time teaching other STEM classes. How much would you like to receive training in this area during the next year? (Select one) (Conditional on response to 16d; 28 only shown if 16d slider response is = 0%)
    a. Not at all, neutral, somewhat, very much

Other Training

29. I need training in socio-emotional skills and learning during the next year (Select one)
    a. Strongly disagree, disagree, agree, strongly agree
30. How much would you like to receive training in socio-emotional skills and learning during the next year? (Select one)
    a. Not at all, neutral, somewhat, very much

31. I need training in online teaching during the next year (Select one)
    a. Strongly disagree, disagree, agree, strongly agree
32. How much would you like to receive training in online teaching during the next year? (Select one)
    a. Not at all, neutral, somewhat, very much
33. I need training in how to facilitate high-quality learning opportunities in STEM classes during the next year (Select one)
    a. Strongly disagree, disagree, agree, strongly agree
34. How much would you like to receive training in how to facilitate high-quality learning opportunities in STEM classes during the next year? (Select one)
    a. Not at all, neutral, somewhat, very much
35. In what other areas, if any, do you need training during the next year? Please be as specific as possible. (text entry)
36. What additional information would you like to share about the training you would like to receive during the next year? (text entry)

Endorsements and Degree Interests

37. Are you interested in pursuing an endorsement? (Select one – yes/no)
38. If 37 = yes then: Which endorsements are you interested in pursuing? (select all that apply)
    a. STEAM, Teacher Leader, Online Teaching
39. If 38 is multiple selected then: Which endorsement would you most prefer to pursue? (Select one)
    a. STEAM, Teacher Leader, Online Teaching
40. Are you interested in pursuing a Master's of Education in Teaching and Learning? (Select one – yes/no)
    a. If yes, which area of specialization would you most prefer to pursue? (Select one)
        i. STEAM, Instructional Coaching, Online Instruction, Effective and Reflective Practitioner

Modality & Timing Preference

41. Training/coursework provided through this program will be online. What is your preferred modality for participation? (Select one)
    a. Online synchronous (participants meet together online at the same time, for example using Zoom or Google Classroom)
    b. Online asynchronous (participants do not meet together online at the same time, but may still interact through discussion boards, etc.)
    c. Online – no preference
42. Some program training/coursework is scheduled to be offered during Clemson's Summer II term, which begins in late June.
    a. Will you be able to participate in Summer 2021? (Select one – Yes, I can start in Summer 2021 / No, I cannot start until Fall 2021)

Wrap-up

43. Please tell us anything else you would like us to know as we develop your *Personalized Advanced Credentials for Teachers* recommendation. (text entry)
44. Was there anything missing from this survey that we should have asked you about? (text entry)
45. How easy was it for you to complete this survey? (Select one)
    a. Difficult, neutral, easy