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What Does the ”Person-Centered Quantitative Approach” Mean in Practice? A Literature Review in STEM Education Research (WIP)

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What Does the "Person-Centered Quantitative Analysis" Mean in Practice? A Literature Review in STEM Education Research (WIP)

Abstract

Background: This work-in-progress paper is a theory-oriented review of the use of person-centered quantitative analysis in STEM education research. Despite ongoing reform efforts, equity remains a central challenge in STEM education, where socioeconomic stratification, structural racism, and gender inequities persist. Traditional variable-centered quantitative methods are effective for identifying average trends but may obscure within-group heterogeneity and reinforce dominant-group norms. Person-centered quantitative analysis offers an alternative by foregrounding individual configurations and subgroup dynamics.

Purpose: The purpose of this review is to synthesize how person-centered quantitative analysis has been applied in STEM education research and how they complement or extend traditional variable-centered analyses. The guiding research question is: In STEM education research, what research questions are addressed using person-centered quantitative analysis, what models are employed, and what key conclusions are drawn?

Methods: Following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, a systematic literature search was conducted using Scopus as the primary database. The initial search, using education-focused keywords and exclusion criteria, yielded 156 articles. After applying additional filters, including publication year (2014–2024), language, article type, and relevance to quantitative, empirical STEM education research focused on students, 13 studies were retained for final review.

Results: The reviewed studies primarily used person-centered approaches to identify learner profiles related to motivation, emotion, cognition, and identity, and to examine their associations with engagement, achievement, and career-related outcomes. Latent Profile Analysis and Latent Class Analysis were the most frequently employed models, often integrated with regression, longitudinal designs, or mixed methods. Findings consistently revealed subgroup-specific patterns, including gendered and cultural differences, as well as dynamic transitions in learner profiles over time.

Future Work: The next step of this study is to expand the literature corpus by incorporating additional databases and refining search strategies to capture a broader range of education-focused publications. We will also attend to emerging computational methods that enable more fine-grained analyses, examining how these developments may shape the operationalization of person-centered quantitative analysis.

Keywords: Engineering Education, STEM Education, Quantitative Methods, Person-Centered Analysis, Latent Profile Analysis, Equity in STEM

Introduction

Despite decades of reform, higher education remains stratified. Institutional structures continue to produce unequal outcomes by race, class, and gender, with high-socioeconomic status (SES) students concentrated in elite institutions [1] and underrepresented groups in STEM marginalized through assimilationist diversity programs [2] and gendered enrollment patterns [3]. Although critical frameworks such as Critical Race Theory (CRT) and Culturally Sustaining Pedagogy challenge these dynamics [4], [5], they are applied primarily in qualitative research.

In quantitative research, variable-centered methods often emphasize broad generalizations. From a QuantCrit perspective, however, numbers are not neutral [6]. Traditional models risk treating social categories as fixed and centering white male students as the normative reference group [7]. Person-Centered Quantitative Analysis (PCA) identifies distinct configurations within individuals and subgroups, moving beyond population-level averages [8]. Scholars have argued that such approaches hold equity-oriented promise by centering the experiences of marginalized populations [9], [10].

This paper reviews the use of PCA in STEM education to expand researchers' methodological repertoires. The guiding research question is: ***In STEM education research, what research questions are addressed using person-centered quantitative analysis, what models are employed, and what key conclusions are drawn?***

Person-Centered Quantitative Analysis

Quantitative research can be grouped into three approaches: variable-centered, person-centered, and person-specific [7]. Variable-centered approaches assume population homogeneity and examine relationships among variables using methods such as regression and structural equation modeling. Person-centered approaches identify subgroups with shared characteristics, using techniques such as latent profile and cluster analysis to capture subgroup-specific dynamics. Person-specific approaches focus on within-individual variability over time, employing methods such as state-space modeling and dynamic factor analysis.

Prior work highlights the distinct value of PCA relative to variable-centered methods. Whereas variable-centered analyses estimate general effects, PCA reveals group-specific patterns [8]. For instance, while regression may generalize the association between SES and achievement, Latent Profile Analysis (LPA) has identified "resilience profiles" that show how particular cognitive and socio-emotional resources support students with low SES [11]. These approaches can also be complementary; combining regression with LPA has uncovered impulsivity profiles related to suicide risk that traditional regression models fail to detect [12].

Although PCA is well established in health and psychology research on behaviors such as sleep [13] and motivation [14], its use in Engineering Education Research (EER) is emerging. Existing studies suggest that PCA can advance equity-oriented research in EER [9]. Recent applications include Topological Data Analysis to identify latent identities [15] and feminist and QuantCrit-informed analyses to interrogate power dynamics in quantitative data [10]. Methodological rigor remains critical; limitations in some models, such as Latent Class Models, have prompted calls for more robust Growth Mixture Models to improve longitudinal model fit [16].

Method

This WIP paper used Scopus as the primary database. The initial search strategy included the following keywords: abstract (person AND centered) AND abstract (science OR technology OR math* OR engineer* OR stem) AND source title (education*) AND NOT source title (psychology) AND NOT source title (nurs* OR pharmaceutical OR medical OR health). Here, "source title" refers to the journal or publication title in which an article appears. In this WIP study, exclusion keywords were applied to precisely target education-focused research. Future work will broaden the scope of the "source title" field to include a more comprehensive body of literature. The initial search yielded 156 articles.

In the second step, we applied several exclusion criteria. We excluded studies published before 2014, non-scholarly journal articles, non-English articles, and review papers, resulting in a dataset of 91 studies. We then conducted a further screening process based on the following criteria: studies that did not involve quantitative analysis, did not focus on students in STEM education, or were not empirical studies. Examples of studies excluded at this stage include those focusing on qualitative analysis or person-centered teaching and learning, and studies examining teacher training programs or focusing on teachers rather than students. 13 studies remained for the final review. Fig. 1 (Appendix A) presents the PRISMA flow diagram.

Findings

Research Aim

A primary focus of the studies is identifying learner profiles based on motivation, emotion, cognition, and identity. For example, studies examined science-related motivation among 15-year-old students [17], [18]. Other research identified motivational profiles in secondary mathematics classrooms [19] and analyzed basic psychological needs profiles of engineering students to assess motivational dynamics [20]. Cognitive-affective profiles of children aged 8 to 10 were also examined [21], as well as emotional profiles of fourth- and fifth-grade primary school students (ages 9–11) in mathematics contexts [22]. Undergraduate engineering students were further grouped based on non-cognitive and affective factors [23], and epistemic knowledge profiles were investigated among high school students [24]. Regarding identity, Information and Communications Technology (ICT) identity profiles among female high school students were explored [25], science identity classifications were examined in relation to hypothesized identity statuses [26], and Inclusive Professional Engineering Identity among first-year engineering students was investigated [27].

Another theme concerns the links between learner profiles and educational outcomes. For example, epistemic profiles were shown to shape learning engagement [24]. Other studies examined how interest influences comprehension of mathematical argumentation [28] and how emotional profiles relate to task values and mathematics achievement [22]. Research also investigated how cognitive-affective profiles (working memory, test anxiety, and self-regulation) relate to mathematical performance [21], and how metacognitive profiles affect mathematical performance [29]. In addition, science and ICT identity profiles were linked to career intentions and related outcomes [18], [25], and science career expectations were examined across different motivation profiles [17].

Studies also investigated how contextual factors shape learner profiles. For instance, emotional profiles were analyzed across countries and grade levels [22]. The effects of interventions, gender, and engineering identity on the stability of IPEI classifications were also examined [27]. Other research explored how instructional practices, engagement, gender, and socioeconomic status influence motivation profiles [17], [18]. Moreover, international experiences and academic engagement were associated with global awareness profiles [30], and situational engagement patterns in science lessons were linked to task values and expectations [31]. Teaching quality was also shown to affect the stability of motivational profiles [19].

Sample and Models

Among younger learners, one study examined 624 Swedish students aged 8 to 10 [21], while another analyzed 6,778 primary-level students from Norway, Portugal, and Serbia [22]. At the middle and high school levels, small-sample studies included 77 Chilean ninth-grade students [31] and 156 high school students from a rural district in Texas [26]. Medium-sized datasets included 631 Taiwanese high school students [24], 708 Singaporean secondary students [29], and 821 female high school students in Hong Kong [25]. Large-scale datasets included 6,020 German students transitioning from Grade 9 to 10 [19], 9,841 Chinese 15-year-old students from 268 schools [18], and 11,583 Italian students from the PISA 2015 dataset [17]. Almost all college-level datasets were drawn from the United States. Sample sizes ranged from small studies with 64 undergraduates [28] to medium-sized datasets of 425 engineering students [30] and 683 first-year engineering students [27]. Larger datasets included 2,339 undergraduate engineering students [23]. Only one study examined a non-U.S. college population, analyzing 1,864 engineering students from the Netherlands [20].

In terms of analytical approaches, most studies used Latent Profile Analysis or Latent Class Analysis (LCA) to identify learner profiles. LPA was commonly applied to group students based on motivational, epistemic, ICT-related, and emotional factors [19], [22], [24], [25]. LCA was used to examine science identity classifications [26], while Gaussian Mixture Modeling clustered students' non-cognitive and affective characteristics [23]. Several studies incorporated additional methods to strengthen analyses. For example, LPA was combined with regression to examine links between metacognitive profiles and academic performance [29]. Longitudinal approaches tracked changes in motivational profiles over time [19], and LPA was integrated with the Experience Sampling Method to capture dynamic engagement in science lessons [31]. Mixed-methods designs were also used, pairing LPA with qualitative interviews to deepen interpretation of profile characteristics [25].

Contribution in the Research Results

The reviewed studies identified diverse learner profiles and demonstrated their links to motivation and engagement. For instance, motivation within basic psychological needs profiles evolved over a semester, with notable changes in autonomy and competence [20]. Three epistemic knowledge profiles were identified, showing that science learning engagement depends not only on knowledge understanding but also on perceptions of certainty and complexity [24]. High situational engagement patterns in science lessons were also strongly associated with higher task values [31].

The studies further demonstrated relationships between learner profiles, educational outcomes, and career expectations. Students with strong self-regulation and working memory outperformed peers with high test anxiety in mathematics [21]. Higher metacognitive regulation and metacognitive knowledge were similarly associated with better mathematics performance [29]. Learners with higher motivation and stronger emotional engagement were more likely to achieve academic success, whereas those with lower self-regulation and higher stress faced greater challenges [23]. Distinct ICT identity profiles were also identified among female students, with stronger ICT identities linked to higher intentions to pursue ICT-related careers [25].

Research additionally identified factors shaping the formation and evolution of learner profiles. Four motivational profiles were identified among secondary students, with classroom characteristics such as teacher support and perceived fairness influencing profile changes over time [19]. Latent Transition Analysis showed that Inclusive Professional Engineering Identity classifications among first-year engineering students were dynamic, with gender and educational interventions shaping transitions between identity profiles [27]. Global awareness among engineering students was also significantly influenced by international experiences and academic engagement [30].

Discussion and Future Work

Most studies classify learner profiles based on subjective characteristics such as motivation, emotion, and identity, while educational outcomes are typically operationalized through standardized measures. Linking subjective profiles to standardized outcomes reflects a pragmatic attempt to move beyond binary thinking in research paradigms [32]. Notably, although equity and QuantCrit motivate this review, most reviewed studies employed PCA for profile identification rather than as an explicitly equity-oriented tool, highlighting an opportunity to integrate PCA with critical frameworks in future research.

The review shows substantial variability in sample sizes, raising concerns about the reliability of findings. Smaller samples (e.g., n = 77) may lack sufficient statistical power to identify distinct subgroups. Conversely, studies using large datasets often rely on pre-existing databases, limiting researchers' control over data collection and reducing flexibility for study-specific goals. In addition, while pre-college datasets are internationally sourced, college-level studies are largely conducted in the United States. This imbalance underscores the need for a more global perspective in higher education research [33]. Methodologically, most studies rely on LPA and LCA [9], with alternative models such as Gaussian Mixture Modeling remaining underutilized. Mixed-methods designs and emerging assessment strategies offer further opportunities for innovation [34], [35].

This review offers an initial mapping of PCA use in STEM education, with implications for future equity-oriented research in engineering education [36]. As a WIP, this review relied solely on Scopus, which may underrepresent studies indexed in ERIC or Web of Science. Future work will expand the scope of the literature by incorporating additional databases and extending the review to interdisciplinary educational contexts. In addition, advances in computational methods, such as topological data analysis [15] and machine learning-based clustering, may reshape how PCA is operationalized and warrant continued attention.

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Appendix A

Fig. 1. PRISMA flow diagram for the literature review [37].