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Profiling Instructors' Acceptance of Feedback Dashboards

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Abstract: This study examined instructors' acceptance of a learning analytics tool (i.e., feedback dashboard) using a person-centered approach grounded in the Technology Acceptance Model (TAM). Prior TAM research has typically adopted variable-centered methods that assume homogeneous perceptions, potentially obscuring qualitative differences among instructors. Latent profile analysis (LPA) was conducted to identify acceptance profiles among instructors. Four profiles emerged: *enthusiastic adopters*, *moderate adopters*, *cautious adopters*, and *resistant adopters*, characterized by progressively lower perceived usefulness, perceived ease of use, and attitudes toward use. Intention to use the dashboards also decreased from *enthusiastic* to *resistant adopters*. The findings highlight the value of person-centered approaches in capturing heterogeneity in instructors' acceptance of analytics tools.

Keywords: learning analytics, technology acceptance, latent profile analysis

1. Introduction

The Technology Acceptance Model (TAM) (Davis et al., 1989) has been widely used to examine instructors' adoption of educational technologies, including learning analytics tools. TAM posits that perceived usefulness and perceived ease of use shape attitudes toward using a technology and, in turn, intention to use. Although prior research supports TAM's explanatory power (e.g., Chan et al., 2024; Lee et al., 2024), most studies rely on variable-centered approaches such as regression and structural equation modeling (SEM) (e.g., Fathema et al., 2015; Masrom, 2007) that assume homogeneity in technology acceptance. Instructors may instead differ in kind rather than merely in degree, forming distinct subgroups with different configurations of perceived usefulness, perceived ease of use, and attitudes toward use.

To address this limitation, this study employs a person-centered approach—latent profile analysis (LPA)—to examine technology acceptance. LPA identifies unobserved subgroups of users who share similar patterns across acceptance-related constructs (Lubke & Muthén, 2005). This approach captures heterogeneity in technology acceptance and offers insights for the design and implementation of learning analytics tools.

Focusing on a feedback dashboard, this study aims to identify distinct acceptance profiles and examine their differences in intention to use. The research questions are:

- RQ1: What latent profiles emerge from perceptions of feedback dashboard?
- RQ2: How does intention to use feedback dashboard differ across profiles?

2. Method

2.1 Feedback Dashboard

This study examined instructors' acceptance of Student Evaluation Analytics (SEA) Dashboard (Lin et al., 2025), a learning analytics dashboard that summarizes and visualizes teaching evaluation scores and topics and sentiments extracted from students' open-ended comments to support instructors' reflection and pedagogical improvement.

2.2 Participants and Procedure

Instructors at a Singapore university who had used the SEA dashboard were invited via email to complete a Qualtrics survey. After providing informed consent, 305 instructors participated (172 male, 132 female, 1 non-binary), with diverse age (20–29 to 70+ years) and teaching experience (>1 year to <20 years). The sample size is sufficient for latent profile analysis (Sinha et al., 2021). The survey took about 10–15 minutes.

2.3 Measures

Demographics included age, gender, and teaching experience. Attitudes toward student feedback were measured using the 11-item ASF scale (Chailis & Lin, 2026) (α = .74–.79). Technology acceptance was assessed using 14 TAM items adapted from Masrom (2007), measuring perceived usefulness, perceived ease of use, attitudes toward use, and intention to use (α = .83–.91). All non-demographic items used a 5-point Likert scale.

2.4 Data Analysis

Latent profile analysis (LPA) was conducted in R (*tidyLPA*) using perceived usefulness, perceived ease of use, and attitudes toward using dashboard as indicators. Solutions with one to four profiles were examined. Solutions with more than four profiles were not considered to avoid overextraction and very small profiles. Model selection was based on lower AIC and BIC values, significant BLRT, entropy (≥ .80), theoretical interpretability, and minimum profile size (≥ 5%). Differences in intention to use across profiles were examined using ANOVA in SPSS.

3. Results

3.1 Latent Profile Analysis

The four-profile solution showed the best fit, with acceptable AIC and BIC, high entropy (.95), and a significant BLRT (see Table 1). The smallest profile included 7% of the sample, exceeding the minimum threshold of 5%. Thus, the four-profile solution was selected. Profiles differed in decreasing levels of perceived usefulness, perceived ease of use, and attitudes toward use (Profile 1 to Profile 4), and were labeled as *enthusiastic adopters, moderate adopters, cautious adopters*, and *resistant adopters* (see Figure 1).

Table 1. *Fit indices for solutions with 1 to 4 profiles. The selected solution is shown in bold.*

	Profiles			
	1	2	3	**4**
AIC	2104.66	1762.02	1602.35	**1366.41**
BIC	2126.98	1799.22	1654.43	**1433.37**
Entropy	1.00	0.87	0.90	**0.95**
BLRT (*p*)	-	0.01	0.01	**0.01**

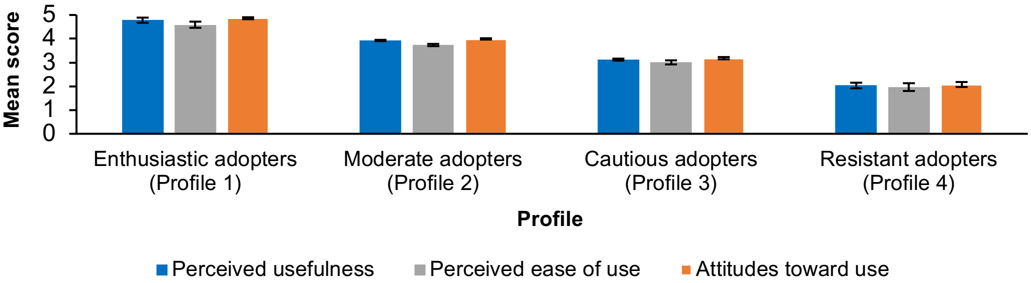

Figure 1. Profile composition

3.2 Differences Across Profiles

A one-way ANOVA was conducted to examine the differences in intention to use dashboards across profiles. Results showed significant differences in intention to use across profiles, $F(3, 301) = 138.32$, $p < .01$, $\eta^2 = 0.58$. All pairwise comparisons (Tukey HSD) were significant (ps $< .001$). Intention to use followed a clear gradient, with *enthusiastic adopters* having the highest intention ($M = 4.46$, $SD = 0.45$), followed by *moderate adopters* ($M = 3.62$, $SD = 0.51$), *cautious adopters* ($M = 2.96$, $SD = 0.45$), and *resistant adopters* ($M = 2.02$, $SD = 0.56$).

4. Discussion

This study extends learning analytics research by applying a person-centered approach to examine instructors' acceptance of feedback dashboards. Using LPA, four profiles emerged: *enthusiastic adopters*, *moderate adopters*, *cautious adopters*, and *resistant adopters*, with decreasing intention to use the dashboard across profiles. These findings highlight qualitative differences among users that are often overlooked in variable-centered studies (e.g., Fathema et al., 2015). Person-centered methods offer value for researchers to uncover heterogeneous acceptance patterns beyond traditional average-effect models. They also help practitioners to identify distinct user groups, enabling targeted interventions and professional development.

Some limitations should be noted. Self-report data may introduce bias, and the cross-sectional, single-institution design limits generalizability and insights into change over time. Future research could use longitudinal and multi-institutional designs to examine how acceptance profiles evolve as learning analytics tools and organizational supports mature.

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