A Latent Profile Analysis of University Faculty Subtypes for Mobile Technology Integration

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ABSTRACT

The need for entirely online instruction as a result of the COVID-19 pandemic has raised many questions about university faculty readiness for online instruction and how to effectively support university faculty in integrating mobile technology into their practice. Previous research suggests subtypes of university faculty technology integration and in turn, a need for diversified approaches to professional development. However, such research is both limited and contested, and thus further research is needed. This multistudy examined whether there are qualitatively distinct faculty subtypes for mobile technology integration (Study 1: N = 83, Study 2: N = 45) based on their knowledge, self-efficacy, and attitudes towards mobile technology, and whether such subtypes, if indeed present, were meaningfully associated with an adoption of mobile technology in the following semester. Findings from the latent profile analysis suggest five university faculty subtypes: Technology Enthusiasts, Knowledgeable Adopters, Prospective Adopters, Knowledgeable Skeptics, and Non-Adopters. Study 2 validates Study 1 findings. Findings illustrate that technology professional development opportunities only have value for certain university faculty groups and that resources would be better targeted elsewhere for faculty groups such as non-adopters. We discuss the implications of these findings for future efforts to support university faculty mobile technology integration.

The movement to entirely online instruction as a result of the COVID-19 pandemic raises important questions about university faculty readiness and their ability and intent to integrate technology into their instruction (134; Martin et al., 2021; 481). Even pre-COVID-19, many researchers sought to understand university faculty technology integration. For example, a review of 148 studies from 2012-2018 illustrates that there is not one simple model for faculty technology integration, that faculty are generally slow to adopt and use technology in a continuous manner, and that technology integration often lacks sufficient connections with evidence-based pedagogy (9). However, as revealed by a review of 44 studies from 2002-2018 (13), there are critical structural and cultural forces that restrain faculty teaching with technology such as faculty career-advancement based on scholarship rather than teaching innovation, teaching with technology being perceived as an unwelcome departure from traditional cultural department norms, and the time intensive nature of learning to effectively teach with technology given other responsibilities (See also (14, 18, 25, 33, 34, 61)).

Beyond structural and cultural factors, faculty members’ own knowledge and perspectives on what constitutes good education within a given context also informs their technology integration (7). Such technology integration can also be underpinned by faculty confidence,

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but such confidence can also be discipline-dependent with science faculty reporting higher confidence than disciplines such as arts and humanities, social sciences, and the health sciences [38]. Specifically, with mobile technology, faculty point to various factors that influence their use, such as social influence, supporting conditions, costs, performance and effort expectancy, hedonic motivation, and habit [24]. For example, nursing faculty using iPads comment positively on opportunities to support more active learning, on the ability to roam more freely amongst students using iPads, and opportunities for new and greater interactions with instructional designers based on iPad use ([54]; performance and effort expectancy). Faculty, in the same study, also note challenges with inconsistent use across instructors of iPads that may confuse students overall, such as instructors using iPads in combination with traditional PowerPoint resources and other instructors using iPads exclusively (social influence). Overall, instructors typically need professional development opportunities to experiment with new technologies, both in and out of their classrooms, while also reflecting on their beliefs about the role of the technologies for student learning [4].

Three important components of technology professional development evaluation involve 1. The type of professional development (delivery mechanism, content, and duration), 2. The unit of analysis (program outcomes, teacher change, student achievement), and 3. Designs and methods (descriptive, case studies, experimental) [31]. The specific focus of this study is on the second stage of professional development evaluation, specifically “teacher change.” Lawless and Pelligrino [31] highlight that the key questions for the second phase, which focuses on teacher outcomes, include examining various outcomes of different approaches to professional development on teachers’ knowledge of technology and technology-integrated pedagogical approaches, attitudes and perceptions including self-efficacy, and technology-related pedagogical behaviors. Therefore, of particular interest is examining the heterogeneity of how university faculty members intend to adopt or not adopt mobile technology by identifying and investigating distinct groups of university faculty members based on their knowledge, self-efficacy, and attitudes related to the use of mobile technology in classrooms.

Key Outcomes: Knowledge, Self-Efficacy, and Attitude

Assessing the key outcomes in the second stage of professional development typically reflects the Bloom’s taxonomy of instructional objectives and have become known as the KAB (i.e., knowledge, attitudes, behaviors) method [31]. Each of the outcomes within the KAB model is also recognized to be comprised of multiple components and to tap several domains. For example, Lawless and Pelligrino [31], p. 606] described that attitudes should measure several constructs, including “the level of importance teachers place on infusing technology into instruction, self-efficacy in using technology in the classroom setting, and perceptions of the influence of new pedagogical approaches on student learning, to name a few.” Outside of the context of assessing outcomes of professional development, several theoretical frameworks have been developed to predict people’s technology-adopting behavior at work. In this study, we integrate the KAB method of assessment of key outcomes in professional development on instructors’ and the Technology Acceptance Model (TAM, ([15], [16])), which is an empirical model that explains why and how people adopt and use modern technologies at work environments. The TAM suggests that behaviors are affected by behavioral intentions, which are affected by two types of attitudes toward technology: perceived usefulness and perceived ease of use of technology. Overall, knowledge, self-efficacy, and attitudes have been emphasized as the key constructs in assessing professional development programs aimed at integrating technology into teaching and learning.

Schraeder and Lawless [52] highlighted that “knowledge embodies all information that a person possesses or accrues related to a particular field of study” (p. 9). There are three different components of knowledge: knowing what something is (declarative knowledge), knowing how it works (procedural knowledge), and knowing when to use it and why it works (conditional knowledge; [52]). In the current study, knowledge refers to the university faculty’s ability to define what mobile technology is (declarative), knowing how a mobile technology works (procedural), and when and why to use mobile technology as a teaching tool (conditional).

Self-efficacy is a person’s belief about their capability to perform a specific task successfully [6], and it is one of the strongest predictors of individual’s behavior. Because low self-efficacy can result in technology avoidance entirely, it is critical to support the continuous development of instructor beliefs about their capability to use mobile technology successfully [8], [34].

Attitude refers to evaluations that people make towards an object or idea, and has three components: the belief or idea associated with the object (cognitive), emotions associated with the object (affective), and the behavior or predisposition to behave towards an object (conative) [52]. In the context of mobile technology, instructors might believe mobile technology is useful for certain classroom practices (cognitive), enjoy using the mobile technology with students (affective), and use the mobile technology to support a particular pedagogy (conative).

Attitudes related to perceived ease of use and perceived usefulness of the new technology have been emphasized in the TAM as two primary factors in self-determining selection technology-adopting behavior ([15], [16]). Perceived ease of use is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” ([15], p. 320). When this construct was defined by Davis, it was assumed that the easier it is for a person to use the system, the more likely they would be to actually adopt and use the system. Perceived usefulness is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” ([15], p. 320). Previous studies have shown that perceived usefulness is a strong predictor of behavioral intention to use technology ([10], [30], [34], [48], [57]). Also, perceived ease of use typically indirectly influences behavioral intention through perceived usefulness (e.g., ([10], [57])) and sometimes directly influences behavioral intention or actual behavior ([30], [57]). Notably, recent studies have proposed that the TAM can be extended with knowledge (e.g., [3]) and self-efficacy (e.g., [19], [20]), showing that both knowledge and self-efficacy play important roles in attitudes towards technology, including ease of use and usefulness, and behavioral intentions to use technology.

Instructors’ knowledge, self-efficacy, and attitudes are complimentary and they address and shape unique aspects of how university faculty members view and integrate or do not integrate mobile technology into their classrooms. Of course, these are not the only variables that can impact technology adoption by instructors. There are additional predictors for instructors and also predictors beyond instructors for technology integration. Various researchers provide teacher-specific typologies to explain factors underpinning technology integration that we summarize in the next section.

Technology Integration Typologies among Instructors

Table 1 provides a summary of literature of the various technology integration typologies that have been identified among instructors. Most of these studies were performed at the K-12 level, with only one study focusing on university faculty (i.e., [23]), thus, highlighting the need for the current study. As summarized, the existing technology integration typologies have included two to five instructor categories that span integration types. Within Table 1, we distinguish the categories across technology knowledge level (high/low), technology self-efficacy (high/low), and technology attitudes (positive/negative). Although these headings may not align completely in all cases, they do highlight the general similarities across the presented studies. Overall, there is an even split of the studies based on sample size with half of the studies containing small samples (less than 50 participants) and half of the
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Studies having larger samples (greater than 50 participants).

There are four studies that use cluster analysis or latent class analysis, which have examined profiles among educators (e.g., [22], [28]; Lamont et al., 2017; [40]; see Table 1). For example, using a large sample of 1246 teachers from 39 schools and focusing on how they adopt a technology integration program into their schools, Lamont et al. (2017) identified five groups of teachers based on how likely teachers were to use personalized, authentic, or collaborative learning and to integrate technology into the classroom: traditional teachers, technology users, PC/NT (personalized and collaborative, no technology), PC/ET (personalized, collaborative, and emerging technology), and early adopters. Traditional teachers were unlikely to use personalized, authentic, or collaborative learning, and were less likely to use technology in the classroom. Teachers in the technology users group were unlikely to use personalized, authentic, or collaborative learning, but were highly likely to integrate technology into the classroom. Teachers in the early adopters group were most likely to use personalized, authentic, and collaborative learning, and were more likely to use technology in the classroom. Teachers in the PC/NT group were highly likely to use personalized and collaborative learning, but were less likely to integrate authentic learning or technology into the classroom. Finally, teachers in the PC/ET group were highly likely to use personalized and collaborative learning, and were likely to integrate some technology into the classroom. Lamont et al. (2017) also examined such variables as professional development quality, level of instruction, provision of devices, special education teacher, years teaching, history of teaching, hours of professional development, and gender. Professional development and provision of devices were found to facilitate program adoption.

Despite the value of technology integration typologies at the K-12 level such as Lamont et al. (2017), university instructors may face distinct challenges to integrating technology compared to K-12 instructors. To the authors’ knowledge, there is only one distinct example of a technology integration typology specific to the university level [23]. In a systematic review of academics’ adoption of learning technologies from 2018 studies and earlier, Liu et al. [34] only identify Rogers’ (1995) typology that is a broader categorization of innovation diffusion. The study by Heinonen et al. [23] is qualitative in nature and focused on 18 university teachers’ reflective writings on their role as technology-enhanced learning developers. Based on this information, there is a gap in the existing literature in terms of quantitative studies for technology integration by university instructors that merits further research. In addition, there is a need for more studies that provide the details and context of their study to allow better comparison of studies on technology adoption as a process rather than an outcome [34]. Lastly, such studies should also include replication studies to ensure their technology integration categorizations are valid, but as with other areas of education and disciplines in general, replication studies are largely absent [56].

The Purpose of the Study

The present study took place within a university-wide university faculty professional development program that focuses on enhancing active-learning pedagogy, affordable learning solutions, and accessible materials through the use of technology. The [Name removed for blind review] program annually provides professional development to approximately 60 new faculty members from the beginning of the Spring semester through a Summer workshop. As part of the program commitments, faculty must then integrate mobile technology into their courses over the following year in order to enhance classroom instruction and learning. We aimed to examine whether there are qualitatively distinct subtypes among faculty members based on their knowledge, self-efficacy, and attitudes towards mobile technology, and to further examine whether such subtypes, if indeed were present, were meaningfully associated with a demographic predictor and an intention to use mobile technology for teaching. Knowing the specific subtypes of faculty members can help with designing professional development that emphasizes different specific components for the different faculty groups.

In Study 1, we used latent profile analysis to derive groups of university faculty based on their self-reported knowledge of mobile technology (mobile technology knowledge), knowledge of integrating mobile technology into one’s content area (mobile technology knowledge integration), self-efficacy towards using mobile technology for teaching (mobile technology self-efficacy), perceptions of ease of use of mobile technology (mobile technology ease of use), perception of usefulness of mobile technology (mobile technology usefulness), attitudes towards teaching with mobile technology (attitude: teaching with mobile technology), attitudes toward students’ learning with mobile technology (attitude: learning with mobile technology), and resistance to adopting mobile technology for teaching (mobile technology resistance). Once the groups were derived, we sought to identify and examine the antecedents and consequences of latent class membership. Specifically, given differences in self-efficacy in technology integration by gender and age (e.g., [2]; Koh & Clark, 2014), we examined whether class prevalence was equivalent by gender and age, and whether the

Table 1: Instructor Category Technology Integration Models

<table>
<thead>
<tr>
<th>Authors/Knowledge, Self-Efficacy and Attitudes</th>
<th>Low Knowledge, Low self-efficacy, negative attitudes</th>
<th>Low knowledge, low self-efficacy, positive attitudes</th>
<th>Low knowledge, high self-efficacy, positive attitudes</th>
<th>High knowledge, high self-efficacy, positive attitudes</th>
</tr>
</thead>
<tbody>
<tr>
<td>[17] (K-12, N = 13) Gestures &amp; Bower, 2018</td>
<td>Contended Traditionalist</td>
<td>Inadvertent User</td>
<td>Selective Adopter</td>
<td>Creative Adopter</td>
</tr>
<tr>
<td>[23] (University, N = 18)</td>
<td>Reluctant Developers</td>
<td>Adaptive Developers</td>
<td>Cautious Developers</td>
<td>Active Developers</td>
</tr>
<tr>
<td>[25] (K-12, N = 18)</td>
<td>Group A – A pivotal tool for self-paced learning</td>
<td>Group B – An additional tool for active and interactive learning</td>
<td>Group C – A tool designed for the integration and assessment of learning</td>
<td>Group D – A tool for changing the learning culture</td>
</tr>
<tr>
<td>[28] (K-12, N = 102) Lamont et al., 2017 (K-12, N = 1246)</td>
<td>Cluster 2 – Less confident than Cluster 1 teachers. Traditional teachers</td>
<td>Cluster 1 – More confident than Cluster 2 teachers. Technology users</td>
<td>PC/NT group</td>
<td>PC/ET group</td>
</tr>
<tr>
<td>Manna &amp; Hennessey, 2013 (K-12, N = 11)</td>
<td>Group D – Moderate to low usage, necessity-focused</td>
<td>Group B – Low to moderate usage, engagement-focused</td>
<td>Group C – High usage, administrative focused</td>
<td>Group A – Moderate to high usage, constructivist-focused</td>
</tr>
<tr>
<td>[40] (K-12, N = 70)</td>
<td>Phase 1 – Professional productivity</td>
<td>Phase 2 – Facilitating and delivering instruction using technology</td>
<td>Phase 3 – Integrating technology into student learning</td>
<td></td>
</tr>
<tr>
<td>[47] (Not applicable; Five Categories) Laggards</td>
<td></td>
<td>Lateness Majority</td>
<td>Early Majority</td>
<td>Early Adopters</td>
</tr>
<tr>
<td>[50] (K-12, N = 200)</td>
<td>Stage 1: Where’s the On Button?</td>
<td>Stage 2: Black Line Mastery</td>
<td>Stage 3: Routine Student Use</td>
<td>Stage 4: What’s in the Curriculum?</td>
</tr>
</tbody>
</table>
latent profiles displayed statistically significant differences in their self-reported intention to use mobile technology in the following semester. For these purposes, we used a sample of two groups of faculty members, one group who self-selected themselves for participation in the [Name removed for blind review] mobile technology professional development program during 2017-18 academic year, and another group who were recruited as a comparison group (a group of faculty members who had never participated in the [name removed for blind review] program).

In Study 2, we derived latent profile groups with a new sample of university faculty (all mobile technology professional development faculty members) with the goal to examine whether we would be able to validate Study 1 findings.

The research questions are summarized as follows:

1. What are distinct faculty profiles for mobile technology integration?
2. Can the distinct faculty profiles be validated with an independent sample of university faculty members through a replication study?

The answer to these questions will be of significant value to the field, as research on the nature of faculty technology integration is limited in general and most studies for technology integration lack a validation of the profiles identified through replication studies. Further, in light of COVID-19 pandemic, greater resources globally are being placed in technology professional development for faculty and such efforts can be guided by the outcomes of this study.

Method

Participants

Participants for Study 1 included 83 (44 female and 39 male) university faculty members, of whom 44 (29 males and 15 females) were self-selected participants in the [Name removed for blind review] mobile technology professional development program during the 2017-18 academic year and 39 (10 males and 29 females) were non-participating in the [Name removed for blind review] program faculty members. The [Name removed for blind review] program is described elsewhere [citation is redacted for blind review] and is not directly relevant to the purpose of this study. Faculty members in the comparison group had never participated in the [Name removed for blind review] program and did not self-select themselves for participation in the [Name removed for blind review] program during that year. Data were only collected from the comparison group of faculty members once. This diverse sample included 32 lecturers, 32 assistant professors, eight associate professors, and 11 full professors, most of whom were full-time (n = 58). In terms of ethnicity/race, 47 self-identified as White, 14 as Latinx, 12 as Asian, two as Black, four as “two or more ethnicities/races,” and four did not specify their ethnicity/race. Faculty members ranged in age from 28 to 70 years (M = 45.7, SD = 11.7).

In Study 2, participants were 45 university faculty members (28 females and 17 males), all of whom were self-selected participants in the [Name removed for blind review] program during the 2018-19 academic year. No data were collected from comparison faculty during this year because this was beyond the scope of the [Name removed for blind review] program. The sample included 12 lecturers, 26 assistant professors, three associate professors, and four full professors. Self-identifications were as follows: 22 White, 11 Latinx, five Asian, one Black, three “two or more ethnicities/races,” and three “not specified.” Most of the participants (n = 38) were full-time. Faculty members ranged in age from 30 to 65 years (M = 43.2, SD = 11.0).

Instruments

Faculty members were asked to complete several scales to assess their self-reported knowledge, self-efficacy, attitudes, and intentions to use mobile technology (see Table 2). The survey used the prompt, “Mobile technology is defined as tablets such as Apple iPad Pro or Surface Pro 4. Please indicate your agreement to each of the following statements,” followed by questions with 7-point Likert-type response scale, ranging from 1 = strongly disagree to 7 = strongly agree. The Instruments (all except for resistance to mobile technology, which was not included in Study 2) were the same across Study 1 and Study 2. The resistance to mobile technology scale was shown to be the least discriminating in Study 1 and, thus, was eliminated from Study 2 to shorten the survey.

Procedure

Ethical approval for this study was obtained according to the University’s policy and procedures on research with human participants. University faculty members were invited to complete the survey, which was administered online in Qualtrics. The link to the survey was emailed to faculty members, and those who did not provide responses after the initial email also received a follow up email with the link to the survey 10 days later. Overall, 66 participating and 156 non-participating in the [Name removed for blind review] program faculty members were contacted through email, and 60 participating and 79 non-participating faculty members opened the link to the survey to read the consent form and decide on whether they wanted to participate. The data collection was completed before the first day of the [Name removed for blind review] program in both Study 1 and Study 2.

<table>
<thead>
<tr>
<th>Instruments</th>
<th># of Items</th>
<th>Adapted from</th>
<th>Example Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>MT knowledge</td>
<td>6</td>
<td>Developed based on the Knowledge about Technology scale [49], the Technological Knowledge scale [53], and the Technology Knowledge subscale [51].</td>
<td>I can learn to use mobile technology easily</td>
</tr>
<tr>
<td>MT integration into content knowledge</td>
<td>5</td>
<td>Developed based on the Information Communication Technology Integration Knowledge scale [49].</td>
<td>I can create learning activities of the content knowledge with appropriate mobile apps</td>
</tr>
<tr>
<td>MT self-efficacy</td>
<td>3</td>
<td>Adapted from Lai [29].</td>
<td>I am confident with my abilities in selecting appropriate apps for teaching with mobile technology</td>
</tr>
<tr>
<td>Ease of use</td>
<td>5</td>
<td>Adapted from the Perceived Ease of Use subscale [30].</td>
<td>It is easy to make mobile technology do what I want it to</td>
</tr>
<tr>
<td>Perceived usefulness</td>
<td>4</td>
<td>Adapted from the Perceived Usefulness subscale [15].</td>
<td>Using mobile technology would enable me to teach more effectively</td>
</tr>
<tr>
<td>Attitude towards teaching with MT</td>
<td>4</td>
<td>Adapted based on the Attitude to Use subscale [30].</td>
<td>Mobile technology makes work more interesting</td>
</tr>
<tr>
<td>Attitude towards learning with MT</td>
<td>7</td>
<td>Adapted from the Attitude and Beliefs subscale [26].</td>
<td>The use of mobile technology increases the permanency of the learning</td>
</tr>
<tr>
<td>MT resistance for using in teaching</td>
<td>5</td>
<td>Technology Resistance scale [27].</td>
<td>I prefer that my students use technology without me</td>
</tr>
<tr>
<td>Intention to use MT</td>
<td>5</td>
<td>Adapted from the Behavioral Intention subscale [41].</td>
<td>Whenever possible, I intend to use mobile technology in my courses.</td>
</tr>
</tbody>
</table>

Note. MT = mobile technology.
Data Analysis

Mixture modeling, a person-centered analytical technique, was applied in this study to derive distinct profiles of the faculty members. Specifically, latent profile analysis, which is a special case of mixture modeling with cross-sectional data when all indicators are continuous ([42]-2017) and used to identify the subgroups that explain the most variance and that provide satisfactory fit with the data ([45]), was used. Faculty profiles were derived based on the measured constructs of knowledge, self-efficacy, and attitude (i.e., mobile technology knowledge, mobile technology integration knowledge, mobile technology self-efficacy, perceived ease of use of mobile technology, perceived usefulness of mobile technology, attitude towards teaching with mobile technology, attitude towards learning with mobile technology, and mobile technology resistance). Several statistical indicators were used to compare models and decide on the final solution (i.e., the number of profiles), including information criteria and the likelihood-based tests (i.e., Bayesian Information Criterion (BIC), sample-size adjusted Bayesian Information Criterion (SBIC)) and the likelihood-based tests (i.e., the Lo-Mendell-Rubin likelihood ratio test (LMRT), [35]) and the bootstrap likelihood ratio test (BLRT, [55]). Information criteria are approximate fit indices, where lower values when different models are compared indicate superior fit. The likelihood-based tests compare the fit of two neighboring profile models and assess whether adding a profile results in a statistically significant improvement in the model fit. The non-significant p-value would signify that the model with fewer profiles is supported. Additionally, we also examined and considered the relative sizes of the emergent profiles (i.e., class prevalence). Due to the relatively low sample size, we were mindful as to avoiding selecting an overextracted profile solution, thus, selecting the solution with at least 8% of the sample in each profile [44]. We also evaluated how well the profiles were differentiated based on the entropy value, which is an omnibus index with values above .80 indicating “good” classification of individuals into profiles [12].

Once profiles were enumerated, we included covariates (i.e., gender and age) to examine whether class prevalence was equivalent across levels of a predictor of class membership, and a distal outcome (i.e., intention to use mobile technology) to examine whether the latent profiles displayed statistically significant mean-level differences in faculty members’ intention to use mobile technology in their classrooms. To do so, a 3-step manual method [5] with covariates (gender, age) and distal outcome (intention to use mobile technology) was used. In this model, enumerated classes, two covariates, and the distal outcomes were specified in one latent model. All analyses were performed in Mplus, Version 8.6 ([43]-2021).

Results

Preliminary Analysis

Table 3 shows the results of reliability analysis and descriptive statistics for Study 1 and Study 2. Reliability estimates were all above .90 except for mobile technology resistance scale in Study 1, which was .80, as well as mobile technology knowledge and intention to use mobile technology in Study 2, which were .77 and .82, respectively. Mean scores were computed for each scale, showing that on average, faculty members had relatively high knowledge, attitudes, and self-efficacy related to using mobile technology for teaching and learning and reported relatively low resistance towards using mobile technology for teaching courses. Mean scores in Study 2 tended to be higher than in Study 1, which was expected given characteristics of the two samples (i.e., Study 1 consisted of both [Name removed for blind review] and non-[Name removed for blind review] program faculty members; whereas Study 2 consisted of only [Name removed for blind review] program faculty members).

Latent Profiles in Study 1

A series of latent profile models were fitted beginning with a 1-profile model up until a 7-profile model, using mobile technology knowledge, mobile technology integration into content knowledge, mobile technology self-efficacy, mobile technology ease of use, mobile technology perceived usefulness, attitudes towards teaching with mobile technology, attitudes towards learning with mobile technology, and mobile technology resistance for teaching as indicator measures. The fit information for these models is presented in Table 4. As is common with mixture models [44], fit indices did not converge on a single solution. The BIC-value indicated the 5- and 6-profile solutions. While the lowest value was not achieved with SABIC, examination of the differences in the values of the sample-adjusted BIC, which compares two neighboring profile models, suggested that the 5-profile solution was plausible. The BLRT suggested that each subsequent solution had a significantly better fit than the preceding solution; whereas the LMRT test indicated the 3-profile solution. Examination of the relative sizes of the emergent profiles (i.e., class prevalence) pointed to the 5-profile solution, because solutions with the 6- and 7-profiles were likely to be overextracted profile solutions. Therefore, we tentatively selected the 5-profile solution and examined profiles for conceptual meaning, plausibility, and the qualitative differences among the profiles. Entropy for the 5-profile solution indicated “good” classification of faculty members into profiles. Average latent class probabilities for most likely latent class ranged from .85 to .96, indicating that the profiles were well-separated. Classification probabilities for the most likely class membership ranged from .79 to .93 (all above .70) and for the non-likely class membership ranged from 0 to .11 (all below .30) indicated high homogeneity. Overall, these results suggested that the profiles were well-separated.

Figure 1 illustrates means for the selected 5-profile solution. The
model indicators are labeled on the x-axis, whereas the y-axis represents the mean scores. The five profiles were defined by the crisscrossing lines, and their preliminary labels are listed at the bottom, with relative profile sizes presented in parenthesis. Table 5 shows descriptive statistics by profile. The first profile was characterized by the highest scores on all indicators and was thus labeled the **Technology Enthusiasts** profile. Faculty members in this profile were likely to be advanced users who knew how to use mobile technology in general as well as were enthusiastic about using mobile technology in classrooms. The second profile was labeled **Knowledgeable Adopters** and was characterized by generally high knowledge, self-efficacy, perceived ease of use and usefulness, and positive attitudes towards mobile technology. The third profile was labeled **Knowledgeable Skeptics** given their similarity with **Knowledgeable Adopters** apart from three indicators of perceived mobile technology uselessness and attitudes towards teaching and learning with mobile technology. Specifically, faculty members in this profile had similar levels of mobile technology knowledge, mobile technology knowledge integration, mobile technology self-efficacy, and perceived ease of mobile technology use to those of **Knowledgeable Adopters**. However, unlike **Knowledgeable Adopters**, faculty members in this profile were generally ambivalent about using mobile technology for teaching and reported significantly lower perceived usefulness of mobile technology, attitude towards teaching with mobile technology, and attitude towards learning with mobile technology compared to **Knowledgeable Adopters**. The fourth

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**Table 4**  
Class Enumeration in Study 1 and Study 2

<table>
<thead>
<tr>
<th># of classes (K)</th>
<th>Log likelihood</th>
<th>BIC</th>
<th>SABIC</th>
<th>( p )-value of BLRT</th>
<th>( p )-value of LMRT</th>
<th>Entropy</th>
<th>Profile Prevalence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1208.1</td>
<td>2486.8</td>
<td>2436.3</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>-1086.5</td>
<td>2283.4</td>
<td>2204.5</td>
<td>(&lt; .001)</td>
<td>.045</td>
<td>.942</td>
<td>.28, .74</td>
</tr>
<tr>
<td>3</td>
<td>-1028.5</td>
<td>2207.2</td>
<td>2100.0</td>
<td>(&lt; .001)</td>
<td>.046</td>
<td>.921</td>
<td>.11, .44</td>
</tr>
<tr>
<td>4</td>
<td>-986.9</td>
<td>2163.7</td>
<td>2028.1</td>
<td>(&lt; .001)</td>
<td>.261</td>
<td>.919</td>
<td>.11, .24, .40, .25</td>
</tr>
<tr>
<td>5</td>
<td>-957.5</td>
<td>2144.7</td>
<td>1980.7</td>
<td>(&lt; .001)</td>
<td>.427</td>
<td>.951</td>
<td>.10, .19, .28, .33</td>
</tr>
<tr>
<td>6</td>
<td>-937.4</td>
<td>2144.4</td>
<td>1952.0</td>
<td>(&lt; .001)</td>
<td>.299</td>
<td>.962</td>
<td>.10, .07, .36, .14, .15, .19</td>
</tr>
<tr>
<td>7</td>
<td>-921.6</td>
<td>2152.4</td>
<td>1931.6</td>
<td>(&lt; .001)</td>
<td>.935</td>
<td>.945</td>
<td>.10, .05, .22, .10, .30, .07, .16</td>
</tr>
<tr>
<td>Study 2</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-510.1</td>
<td>1073.5</td>
<td>1029.6</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>-445.6</td>
<td>974.9</td>
<td>905.9</td>
<td>(&lt; .001)</td>
<td>.062</td>
<td>.941</td>
<td>.56, .44</td>
</tr>
<tr>
<td>3</td>
<td>-404.8</td>
<td>928.9</td>
<td>829.9</td>
<td>(&lt; .001)</td>
<td>.134</td>
<td>.991</td>
<td>.16, .49, .35</td>
</tr>
<tr>
<td>4</td>
<td>-375.3</td>
<td>918.7</td>
<td>799.5</td>
<td>(&lt; .001)</td>
<td>.441</td>
<td>.984</td>
<td>.49, .25, .16, .11</td>
</tr>
<tr>
<td>5</td>
<td>-365.0</td>
<td>935.6</td>
<td>766.3</td>
<td>.072</td>
<td>.469</td>
<td>.987</td>
<td>.49, .77, .11, .09, .04</td>
</tr>
<tr>
<td>6</td>
<td>-365.0</td>
<td>935.6</td>
<td>766.3</td>
<td>.072</td>
<td>.469</td>
<td>.987</td>
<td>.49, .22, .12, .09, .07, .02</td>
</tr>
</tbody>
</table>

Note: BIC = Bayesian Information Criterion; SABIC = sample adjusted Bayesian Information Criterion; BLRT = the bootstrap likelihood ratio test; LMRT = the Lo-Mendell-Rubin likelihood ratio test. Plausible solutions based on each fit index are in boldface.
profile was labeled **Prospective Adopters** given their similarity with *Knowledgeable Adopters* on three indicators of perceived uselessness and attitudes. Faculty members in this profile were characterized by generally low mobile technology knowledge, mobile technology knowledge integration, mobile technology self-efficacy, and perception of ease of mobile technology use. Yet, similar to *Knowledgeable Adopters, Prospective Adopters* were also characterized by generally positive attitudes towards the use mobile technology for teaching and reported similar to *Knowledgeable Adopters*’ levels of perceived usefulness of mobile technology, attitude towards teaching with mobile technology, and attitude towards learning with mobile technology. Finally, the fifth profile was labeled **Non-Adopters** given the characteristically low means for all model indicators.

Examination of profiles by [Name removed for blind review] program participation status showed that the **Non-Adopters** profile consisted entirely of the non-[Name removed for blind review] program faculty members (all non-participating faculty members). As well, compared to non-participating faculty members, self-selected intervention faculty were three times more likely to be in the **Prospective Adopters** profile than in the **Knowledgeable Skeptics** profile (OR = 3.00, p = .019).

In the next step, covariates (gender, age) and the distal outcome (intention to use mobile technology) were added to the latent model using a 3-step manual method [5]. It was more likely that older faculty members were **Non-Adopters** rather than **Knowledgeable Adopters** (OR = 1.12, p = .001), **Technology Enthusiasts** (OR = 1.17, p < .001), and **Knowledgeable Skeptics** (OR = 1.14, p = .001). Older faculty members were also more likely to be in the **Prospective Adopters** profile than in the **Technology Enthusiasts** profile (OR = 1.13, p = .016). Holding age constant, it was more likely that female faculty members were in the **Prospective Adopters** profile than in the **Knowledgeable Adopters** profile (OR = 3.57, p = .004) and in the **Knowledgeable Skeptics** profile (OR = 2.92, p = .044). After controlling for gender and age, significant differences emerged among profile groups on intentions to use mobile technology, as indicated by the Wald test of parameter constraints, $\chi^2(4, N = 83) = 436.32, p < .001$. Specifically, **Technology Enthusiasts** reported the highest levels of intentions to use mobile technology ($M = 6.28, SE = .09$) compared to all other profiles ($p < .001$). While no differences emerged between **Knowledgeable Adopters** ($M = 5.41, SE = .013$) and **Prospective Adopters** ($M = 4.99, SE = .30$), $p = .203$, they reported higher intentions to use mobile technology than **Knowledgeable Skeptics** and **Non-Adopters**, $p < .006$. **Knowledgeable Skeptics** were generally ambivalent in intentions to use mobile technology ($M = 4.08, SE = .015$), but had statistically significantly higher intentions than **Non-Adopters** ($M = 1.93, SE = .17, p < .001$), who were generally quite unlikely to use mobile technology.

### Latent Profiles in Study 2

Latent profile models were fitted for up to six profiles based on indicators of mobile technology knowledge, mobile technology integration into content knowledge, mobile technology self-efficacy, mobile technology ease of use, mobile technology perceived usefulness, attitudes towards teaching with mobile technology, and attitudes towards learning with mobile technology. Table 4 shows the fit indices. The BIC value, the BLRT test, and class prevalence pointed to the 4-profile solution. For the 4-profile solution, the classification of faculty members into profiles was generally quite unlikely to use mobile technology for teaching in the coming semester. **Knowledgeable Skeptics** were generally ambivalent in intentions to use mobile technology ($M = 4.43, SE = .27$), and scored the lowest among the four profiles on intentions to use mobile technology than other profiles, $p < .002$.

<table>
<thead>
<tr>
<th>Technology Adoption Profile (% in class)</th>
<th>MT Knowledge Integration (5.53$^a$ (0.31))</th>
<th>MT Knowledge Self-Efficacy (6.02$^b$ (0.26))</th>
<th>MT Ease of Use (6.15$^c$ (0.24))</th>
<th>MT Usefulness with MT (6.63$^d$ (0.12))</th>
<th>Attitude: Teaching with MT (6.68$^e$ (0.12))</th>
<th>Attitude: Learning with MT (6.25$^f$ (0.15))</th>
<th>MT Resistance (2.02$^g$ (0.29))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Technology Enthusiasts (28.2%)</td>
<td>5.94$^a$ (0.32)</td>
<td>5.12$^c$ (0.20)</td>
<td>5.01$^c$ (0.20)</td>
<td>4.98$^d$ (0.28)</td>
<td>3.83$^e$ (0.17)</td>
<td>3.76$^e$ (0.14)</td>
<td>3.77$^e$ (0.26)</td>
</tr>
<tr>
<td>2. Knowledgeable Adopters (32.8%)</td>
<td>4.98$^e$ (0.21)</td>
<td>5.20$^c$ (0.21)</td>
<td>5.30$^c$ (0.19)</td>
<td>5.45$^c$ (0.13)</td>
<td>5.10$^c$ (0.16)</td>
<td>2.85$^c$ (0.22)</td>
<td></td>
</tr>
<tr>
<td>3. Knowledgeable Skeptics (19.3%)</td>
<td>4.44$^e$ (0.27)</td>
<td>4.39$^c$ (0.34)</td>
<td>4.25$^c$ (0.51)</td>
<td>6.13$^c$ (0.23)</td>
<td>5.26$^c$ (0.21)</td>
<td>5.36$^c$ (0.26)</td>
<td>3.07$^c$ (0.34)</td>
</tr>
<tr>
<td>4. Prospective Adopters (9.9%)</td>
<td>2.96$^e$ (0.18)</td>
<td>2.85$^c$ (0.41)</td>
<td>2.49$^c$ (0.41)</td>
<td>6.13$^c$ (0.23)</td>
<td>5.26$^c$ (0.21)</td>
<td>5.36$^c$ (0.26)</td>
<td>3.07$^c$ (0.34)</td>
</tr>
<tr>
<td>5. Non-Adopters (9.6%)</td>
<td>1.81$^e$ (0.20)</td>
<td>2.15$^c$ (0.27)</td>
<td>1.75$^c$ (0.15)</td>
<td>2.68$^c$ (0.32)</td>
<td>1.81$^c$ (0.24)</td>
<td>2.53$^c$ (0.20)</td>
<td>2.70$^c$ (0.36)</td>
</tr>
</tbody>
</table>

**Table 5** Descriptive Statistics by Profile in Study 1

Note. MT = mobile technology. Superscript letters indicate significant differences across cluster groups for each variable based on the post hoc tests multiple pairwise comparisons, $p < .05$. 

integration, mobile technology self-efficacy, and perception of ease of mobile technology use. Yet, similar to *Knowledgeable Adopters, Prospective Adopters* were also characterized by generally positive attitudes towards the use mobile technology for teaching and reported similar to *Knowledgeable Adopters*’ levels of perceived usefulness of mobile technology, attitude towards teaching with mobile technology, and attitude towards learning with mobile technology. Finally, the fifth profile was labeled **Non-Adopters** given the characteristically low means for all model indicators.

Examination of profiles by [Name removed for blind review] program participation status showed that the **Non-Adopters** profile consisted entirely of the non-[Name removed for blind review] program faculty members (all non-participating faculty members). As well, compared to non-participating faculty members, self-selected intervention faculty were three times more likely to be in the **Prospective Adopters** profile than in the **Knowledgeable Skeptics** profile (OR = 3.00, p = .019).

In the next step, covariates (gender, age) and the distal outcome (intention to use mobile technology) were added to the latent model using a 3-step manual method [5]. It was more likely that older faculty members were **Non-Adopters** rather than **Knowledgeable Adopters** (OR = 1.12, p = .001), **Technology Enthusiasts** (OR = 1.17, p < .001), and **Knowledgeable Skeptics** (OR = 1.14, p = .001). Older faculty members were also more likely to be in the **Prospective Adopters** profile than in the **Technology Enthusiasts** profile (OR = 1.13, p = .016). Holding age constant, it was more likely that female faculty members were in the **Prospective Adopters** profile than in the **Knowledgeable Adopters** profile (OR = 3.57, p = .004) and in the **Knowledgeable Skeptics** profile (OR = 2.92, p = .044). After controlling for gender and age, significant differences emerged among profile groups on intentions to use mobile technology, as indicated by the Wald test of parameter constraints, $\chi^2(4, N = 83) = 436.32, p < .001$. Specifically, **Technology Enthusiasts** reported the highest levels of intentions to use mobile technology ($M = 6.28, SE = .09$) compared to all other profiles ($p < .001$). While no differences emerged between **Knowledgeable Adopters** ($M = 5.41, SE = .013$) and **Prospective Adopters** ($M = 4.99, SE = .30$), $p = .203$, they reported higher intentions to use mobile technology than **Knowledgeable Skeptics** and **Non-Adopters**, $p < .006$. **Knowledgeable Skeptics** were generally ambivalent in intentions to use mobile technology ($M = 4.08, SE = .015$), but had statistically significantly higher intentions than **Non-Adopters** ($M = 1.93, SE = .17, p < .001$), who were generally quite unlikely to use mobile technology.

### Latent Profiles in Study 2

Latent profile models were fitted for up to six profiles based on indicators of mobile technology knowledge, mobile technology integration into content knowledge, mobile technology self-efficacy, mobile technology ease of use, mobile technology perceived usefulness, attitudes towards teaching with mobile technology, and attitudes towards learning with mobile technology. Table 4 shows the fit indices. The BIC value, the BLRT test, and class prevalence pointed to the 4-profile solution. For the 4-profile solution, the classification of faculty members into profiles was generally quite unlikely to use mobile technology for teaching in the coming semester. **Knowledgeable Skeptics** were generally ambivalent in intentions to use mobile technology ($M = 4.43, SE = .27$), and scored the lowest among the four profiles on intentions to use mobile technology than other profiles, $p < .002$.
The purpose of this study was to examine whether there are qualitatively distinct profiles among university faculty members based on their knowledge, self-efficacy, and attitudes towards mobile technology (Research Question 1), and to establish the validity of these profiles through a replication study (Research Question 2). For these purposes, mixture modeling, a person-centered analytical technique, was applied in this study to derive latent profiles of university faculty members using several indicators, including mobile technology knowledge, mobile technology knowledge integration, mobile technology self-efficacy, ease of mobile technology use, mobile technology usefulness, attitudes towards teaching with mobile technology, attitudes towards learning with mobile technology, and mobile technology resistance. Findings indicated five distinct profiles of university faculty members overall: Technology Enthusiasts, Knowledgeable Adopters, Knowledgeable Skeptics, Prospective Adopters, and Non-Adopters. The five profiles emerged in Study 1 (Research Question 1), whereas Study 2 provided validation to the profiles that emerged in Study 1 (Research Question 2).

Two important findings stand out when examining characteristics across profiles in Study 1 and Study 2. First, university faculty members who reported higher levels of perceived usefulness and more positive attitudes towards mobile technology also reported higher levels of intentions to adopt mobile technology in the following semester (e.g., Technology Enthusiasts, Knowledgeable Adopters, Prospective Adopters). The connection between attitudes and intentions to use mobile technology was especially apparent among university faculty members in the Prospective Adopters profile, who reported generally low knowledge, self-efficacy, and perceived ease of use, but generally high perceived usefulness, positive attitudes, and generally high intentions to use mobile technology in the following semester. Secondly, Non-Adopters, the profile that consisted entirely of the non-participating in the [Name removed for blind review] program faculty members, did not emerge in Study 2. Yet, the other four profiles (i.e., Technology Enthusiasts,...

### Table 6
Descriptive Statistics by Profile, Study 2

<table>
<thead>
<tr>
<th>Technology Adoption Profile (%) in class</th>
<th>MT Knowledge</th>
<th>MT Knowledge Integration</th>
<th>MT Self-Efficacy</th>
<th>MT Ease of Use</th>
<th>MT Usefulness</th>
<th>Attitude: Teaching with MT</th>
<th>Attitude: Learning with MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Technology Enthusiasts (48.9%)</td>
<td>5.50^a (0.18)</td>
<td>6.17^a (0.19)</td>
<td>6.37^a (0.17)</td>
<td>6.25^a (0.21)</td>
<td>6.70^a (0.08)</td>
<td>6.90^a (0.05)</td>
<td>6.65^a (0.09)</td>
</tr>
<tr>
<td>2. Knowledgeable Adopters (24.6%)</td>
<td>4.81^b (0.21)</td>
<td>5.14^ab (0.53)</td>
<td>5.66^b (0.24)</td>
<td>5.73^b (0.24)</td>
<td>5.41^b (0.18)</td>
<td>5.53^b (0.11)</td>
<td>5.32^b (0.17)</td>
</tr>
<tr>
<td>3. Knowledgeable Skeptics (15.6%)</td>
<td>4.45^ac (0.34)</td>
<td>4.91^ac (0.37)</td>
<td>4.91^ac (0.56)</td>
<td>5.60^ac (0.48)</td>
<td>4.29^ac (0.30)</td>
<td>3.79^ac (0.17)</td>
<td>3.74^ac (0.33)</td>
</tr>
<tr>
<td>4. Prospective Adopters (11.0%)</td>
<td>3.58^d (0.39)</td>
<td>3.68^d (0.74)</td>
<td>2.39^d (0.53)</td>
<td>3.73^d (0.66)</td>
<td>5.85^d (0.09)</td>
<td>5.49^d (0.17)</td>
<td>5.30^d (0.17)</td>
</tr>
</tbody>
</table>

Note. MT = mobile technology. Superscript letters indicate significant differences across cluster groups for each variable based on the post hoc tests multiple pairwise comparisons, \( p < 0.05 \).
Knowledgeable Adopters, Knowledgeable Skeptics, Prospective Adopters) did emerge in Study 2. In Study 1, we surveyed university faculty members from both a group of faculty members who self-selected to participate in a semester/summer-long mobile technology professional development and a comparison group of faculty members who had never participated in the [Name removed for blind review] program. In Study 2, on the other hand, we surveyed university faculty members from a [Name removed for blind review] program group only. Therefore, because Non-Adopters consisted entirely of non-participating faculty members, and because the other four profiles emerged in both Study 1 and Study 2, findings provide validation of the derived profiles.

While we are not aware of another study that employed a person-centered approach using perceived usefulness and ease of use as indicators to derive groups, previous variable-centered studies have shown that perceived usefulness is a strong predictor of behavioral intention to use technology ([30], [48]). Findings in our study provide further evidence of this connection. In some previous studies, it was shown that perceived ease of use typically indirectly influences behavioral intention through perceived usefulness (e.g., ([10], [57]) and sometimes directly influences behavioral intention or actual behavior ([30], [57]). Yet, in our study, findings showed that perceived ease of use of mobile technology was connected with self-reported intentions to use mobile technology for teaching for some university faculty members (i.e., in the Technology Enthusiasts, Knowledgeable Adopters, and Non-Adopters profiles), but not for all (i.e., Prospective Adopters), which might explain conflicting findings between perceived ease of use and behavioral intentions in previous studies.

Findings showed that older adults were overrepresented in two groups: Non-Adopters and Prospective Adopters, with both profiles reporting generally low knowledge, self-efficacy, and ease of use of mobile technology. While higher level of education, which is a characteristic of university professors, has been shown to be positively correlated with higher technology adoption ([39], older adults experience changes in social connection, and generally lower motivation that influence technology adoption ([32]) and tend to have different concerns, needs, competencies, and abilities with technology ([11]). Meleenhorst et al. ([37]) suggest that adoption of technology by older adults is based in two types of motivation: direct positive motivation (i.e., benefits and the absence of costs) and direct negative motivation (costs and absence of benefits). Likewise, a study by Wang et al. ([58]) showed that intrinsic motivation, requisite knowledge, and anxiety were primarily factors influencing mobile phone adoption by older adults. In other words, and as shown in our study, when older university faculty fail to see the benefits of using mobile technology from the onset, they are less likely to be interested in using a technological tool and to participate in professional development aimed at integrating mobile technology into classes. A grounded theory study by Wang et al. ([59]) found that during the preadoption stage, most older adults want to stay updated, maintain self-image, and reduce the technology gap between them and their family to improve parent-child relationships. However, they were found to be affected by their negative perception of technological product. Similarly, in our study, what distinguished Non-Adopters and Prospective Adopters was how they perceived utility and worth of technology for the use in a classroom. Older adults are a group that typically is not specifically addressed by university professional development or technology programs, and thus further research is merited ([36]).

Practical Implications of This Study

Literature has long recognized ineffectively developed professional development opportunities as the primary reason for the lack of technology integration among instructors (e.g., [46]). Recent studies continue to demonstrate that faculty can be slow to adopt and to continually use technology to support evidence-based pedagogy ([9], [13]). An important goal of this study was to establish university faculty profiles in order to find practical ways to improve mobile technology professional development. Our findings illustrated a spectrum of experiences in faculty adoption and use of technology in their practice. In particular, our findings point to the importance of faculty attitudes and to strategies that are considerate of faculty members’ knowledge, self-efficacy, and attitudes.

We found that attitudes are closely related to intentions to use mobile technology, more so than knowledge. This outcome is important in designing professional development, because this suggests that professional development should provide not only knowledge and skills to faculty, but also aim at understanding faculty members’ attitudes towards technology. The understanding of attitudes can help place outcomes of technology adoption from a neutral and broader viewpoint, rather than viewing adoption as the only desirable outcome of professional development ([34]). Such professional development may inform other aspects of faculty practice such as evidence-based pedagogical approaches that may not require technology to be successfully enacted. Notably, the salient role of attitudes and beliefs on instructors’ use of technology in professional development has been highlighted almost a decade ago ([46]). Yet, our study points to the heterogeneity in faculty’s attitudes and their future behaviors as evident by the five groups identified in this study, suggesting that each group requires distinct considerations for mobile technology professional development, which also aligns with prior calls for diverse forms of professional development for instructors ([17], [60]).

Because Technology Enthusiasts score high across all categories, they, thus, can be positive change agents within professional development, as teachers listen most to other teachers ([21]). Professional development programs should plan to identify such faculty so that they can be distributed across working groups, and thus positively influence other faculty. Likewise, Knowledgeable Adopters could also be used in a similar manner. Prospective Adopters, on the other hand, have positive attitudes and intentions to use mobile technology, but low knowledge. Research has suggested that the absence of innovators and early adopters negatively impacts the likelihood of technology adoption by instructors ([1]). Therefore, professional development, supported by Technology Enthusiasts and Knowledgeable Adopters, focused on showing “how” to use mobile technology and providing practical knowledge and skills would be especially helpful for Prospective Adopters.

Knowledgeable Skeptics reported somewhat appropriate general knowledge of mobile technology, but they seemed to not have entirely “bought-in” into the idea of using mobile technology for teaching and learning. They also reported ambivalent levels of intentions to use mobile technology for teaching and learning. Previous studies have identified such stakeholders as cautious ([23], assessors ([22], selective ([17], and so forth. Importantly, such resistors ([21]) can provide valuable insight for improved technology use. Thus, this group would especially benefit from professional development that elicits the underlying reasons for their attitudes towards using mobile technology for teaching and learning, and helps positively address, where possible, challenges associated with these reasons.

Finally, our findings showed that the Non-Adopters group consisted entirely from non-participating in mobile technology professional development university faculty members. This important finding points to characteristics of faculty members who are against adopting mobile technology, that they seem to be very unmotivated to and would be very unlikely to participate in mobile technology professional development opportunities (regardless of the effort and incentives provided). This faculty profile was also more likely to include older faculty members compared to all other profiles and in general pointed to more traditionalistic faculty members. Mobile technology professional development is unlikely to attract such faculty, nor should it be expected ([34]). Hence, targeting them through other forms of professional development that addresses other pedagogical needs may offer more fruitful outcomes. As well, it is important to consider overall how older adults specifically can be better served by professional development.

In sum, we know that there is variability in university faculty
members’ knowledge, attitudes, and skills of using mobile technology in general and for teaching specifically. The overall take-away point is that professional development programs should be designed in a way that they are conscious of the needs of various groups of faculty members in order to be most effective and result in greater technology-integration among university faculty. The biggest value of this study is that while there have been recommendations in the literature for diverse forms of professional development for different faculty needs, such professional development is difficult to implement without understanding university faculty subtypes. The typology offered in this study allows professional development opportunities to be targeted in very clear ways based on the type of faculty identified. Given our typology is more targeted, university resources can be better spent by administrators and learning institutes in universities. 

Taken together, the following recommendations are derived for professional development from the faculty subtypes for mobile technology integration:

1. Engage in need analysis in terms of faculty’s knowledge, self-efficacy, and attitudes.
2. Provide well-thought professional development content that reflects needs of the university faculty groups.
3. Provide opportunities that foster collaboration among university faculty members during the professional development.
4. Conduct assessment of the professional development effectiveness with focus on knowledge, self-efficacy, and attitudes.
5. Implement faculty learning communities for continuous support and collaboration among university faculty members.

Theoretical Implications

While the purpose of this study was not to develop a new theory, we integrated the KAB model and the TAM, which are typically applied to assessment of professional development in integrating technology into teaching and learning [31] and to understanding self-determining selection technology-adopting behavior at work environments ([15], [16]), respectively. The two models overlap in that they both consider attitudes as a salient factor in determining behavior. In the assessment of professional development literature, the knowledge component has long been recognized as a main outcome. Recent studies utilizing the TAM has also incorporated knowledge (e.g., [3]) and self-efficacy (e.g., [19], [20]). This study provides additional support of the importance of including both knowledge and self-efficacy in addition to attitudes in examining the process of integrating technology among adult workers.

Limitations and Strengths

The first limitation is that person-centered approaches are prone to sample-dependent findings, which might limit the generalizability of these profiles. Yet, unlike traditional person-centered descriptive and non-inferential techniques, such as a split procedures or cluster analysis, latent profile analysis is a model-based analytical technique that uses fit indices and statistical tests to compare competing models and select the final solutions, which is a strength of the current study. Additionally, Study 2 validated the profiles that were derived in Study 1 with a new independent sample of university faculty members. For the purposes of identifying profiles, the faculty members in this study were diverse in their backgrounds (gender, age). Hence, the results of this multi-study provide an important insight into understanding the experiences of faculty members, which might affect how they integrate mobile technology in their instruction. In addition, our findings illustrate the replicability of our approach. Thus, our findings would be of value to other researchers, administrators, and technology developers, seeking to establish the profiles of their professional development participants, and to target resources effectively and realistically.

Second, this study was based on cross-sectional data; thus, no causal conclusions can be drawn. This multi-study suggested that distinct subtypes of university faculty members exists and that there are differences across these profiles on self-reported intentions to use mobile technology in classrooms after covarying for gender and age. Third, behavioral intentions, while much used in the TAM studies, are not the same as actual behaviors. Future studies should seek to measure behaviors, which can be done through multiple means, such as self-reported behaviors, observational studies, reports by other informants. As well, relatively small sample sizes in the two studies is also a limitation. Yet, no previous study that we are aware of exists that applied a person-centered approach of latent profile analysis at the higher educational level to derive unique profiles of faculty members in technology adoption.

A major strength of this research is that this was a multi-study with two studies that were conducted to explore distinct groups of university faculty members. Another strength of this research is that Study 1 was designed in a way that it included a diverse sample of faculty members because participants were drawn from two very different target populations: a group of faculty members who are inherently interested in learning more about mobile technology by self-selecting to participate in the [Name removed for blind review] mobile technology professional development program and a comparison group of faculty members who had not participated in the [Name removed for blind review] program and likely included diverse participants (i.e., those who just happened to not yet enroll in this annually offered professional development and those who purposefully avoid or are uninterested and unmotivated in learning more about ways to use novel technologies in their classrooms).

Conclusions

In sum, the purpose of this study was to examine the adoption of mobile technology for teaching across the distinct subtypes of university faculty members for mobile technology integration based on their knowledge, self-efficacy, and attitudes. Findings from the latent profile analysis in Study 1, which were also validated in Study 2, suggested five faculty subtypes: Technology Enthusiasts, Knowledgeable Adopters, Prospective Adopters, Knowledgeable Skeptics, and Non-Adopters. Findings also showed that some groups, such as Non-Adopters, appear to be opposed to adopting mobile technology. The other four groups seem to be open to mobile technology per se, but they vary in terms of their willingness to adopt and integrate it in their classrooms. Findings in this study can inform administrators and institutional bodies on how to reach out to a larger group of faculty members and provide the most relevant professional development to various groups of faculty members. An important consideration based on these findings is that mobile technology professional development programs can be designed in a way that they would emphasize different components for the different university faculty groups.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References


