EVALUATION OF OPEN AND DISTANCE LEARNER PROFILE IN THE CONTEXT OF LEARNING STRATEGIES: AN ANALYSIS OF THE LATENT PROFILE IN TERMS OF DEEP AND SURFACE LEARNERS

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ABSTRACT

The rapid evolution of digital technologies has significantly transformed educational methodologies, particularly in open and distance learning environments. Employing a quantitative, cross-sectional design, the study applies Latent Profile Analysis (LPA) to data collected from 1,045 students enrolled in the open education faculty at Anadolu University, Turkiye. This study investigates the latent profiles of open and distance learners in terms of their learning strategies, focusing on deep and surface learning approaches, and their perceptions of technology acceptance and barriers. Utilizing Latent Profile Analysis (LPA), the research identifies three distinct learner profiles: *preservers*, *prudents*, and *pioneers*. These profiles are characterized by varying levels of intrinsic technology barriers and technology acceptance. The findings reveal significant differences in deep and surface learning strategies among these profiles, with pioneers exhibiting higher technology adoption and deep learning engagement, while preservers show greater resistance to technology and a tendency toward surface learning. The study underscores the importance of understanding these profiles to design adaptive digital learning environments that cater to diverse learner needs. It also highlights the role of psychological, motivational, and contextual factors in shaping technology adoption and learning behaviors. Practical implications include the development of targeted interventions, such as user-friendly platforms for preservers and advanced tools for pioneers, to enhance technology acceptance and promote deep learning strategies. The study enriches digital learning ecosystem discourse by applying Diffusion of Innovations Theory and highlighting the need for personalized, inclusive experiences in open and distance learning.

Keywords: Open and distance learning, deep learning, surface learning, technology acceptance, latent profile analysis, diffusion of innovations theory, learner profiles.

INTRODUCTION

The digital era has reshaped learning through the rapid integration of diverse technologies. Advances in digital tools have transformed educational methods and environments, prompting a reevaluation of learning approaches. As digital technologies proliferate, psychological factors such as anxiety and attitudes significantly affect how individuals engage with them (Giacomo et al., 2019; Venkatesh & Davis, 2000). Anxiety can create barriers, while positive attitudes encourage acceptance and shape behavioral intent. Research highlights that technological developments have profoundly influenced pedagogical practices, offering both opportunities and challenges for educators (Hussain et al., 2024). The study is informed by Rogers' (1995) Diffusion of Innovations (DOI) and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks in explaining technology adoption.

Although technology acceptance, perceived barriers to technology integration, and learning approaches have each been widely examined in the open and distance learning (ODL) literature, previous studies have predominantly relied on variable-centered approaches. Such approaches clarify relationships among variables but offer limited insight into learner heterogeneity—the ways in which individual ODL learners systematically differ in their psychological readiness, perceptions of technology, motivation, and learning strategies.

Furthermore, while researchers have separately investigated technology adoption models (e.g., UTAUT), barriers to technology integration, and deep and surface learning approaches, limited empirical evidence exists on how these dimensions interact simultaneously to generate distinct learner profiles. It remains unclear, for example, whether learners who engage in deep learning are necessarily more willing to accept digital technologies, or whether technology adoption follows different patterns depending on individual learner characteristics.

Revisiting educational methodologies in light of digital ecosystems requires a comprehensive understanding of how pedagogical approaches adapt to rapidly evolving technologies. This shift involves not merely acquiring new tools but fundamentally restructuring learning processes within hyperconnected systems. Accordingly, digital pedagogies must be reconsidered so that they constitute the core logic guiding the educational use of tools and technologies.

This avenue of inquiry centers on the concept of learning ecologies, encompassing the various contexts and resources that learners interact with in both physical and digital environments. Drawing on Saari's (2021) analysis, discourses on flexible learning environments can be seen as part of a broader "modular" logic of governance, in which school spaces are organized through ever-shifting assemblages of technologies, materials and discourses rather than fixed classroom units. The design allows for addressing the different and specific learning needs of learners in the digital age. Such ecosystems are constantly changing and therefore, learners need to develop self-regulation skills. As Khalil et al. (2024) emphasizes, self-regulated learning is an essential prerequisite for students to succeed effectively in adaptive digital learning environments. Therefore, these self-regulatory skills must be deliberately developed and reinforced among students, rather than assumed as inherent.

Building on these discussions, this study investigates latent variables underlying learning approaches in digital environments, with particular attention to psychological, motivational, and contextual determinants of technology adoption and interaction. Using latent profile analysis (LPA), it identifies distinct learner profiles based on technology acceptance, intrinsic technology barrier perceptions, and deep and surface learning strategies. Classifying distance learners by learning-strategy profiles will enable subsequent alignment of course content with these profiles, thereby promoting more durable learning. Specifically, this study seeks to address the following research questions:

1. What is the implicit profile structure of open and distance learners with different learning strategies in terms of technology acceptance and intrinsic technology barrier perception?
2. Does the implicit profile structure of open and distance learners differ in terms of deep learning strategies?
3. Does the implicit profile structure of open and distance learners differ in terms of surface learning strategies?

LITERATURE REVIEW

Theory of Diffusion of Innovations in Education and Technology Adoption

Rogers' (1995) DOI theory offers a foundational lens for understanding how new technologies and methods are adopted in education. Adoption is shaped by perceived innovation attributes—relative advantage, compatibility, complexity, trialability, and observability—as well as communication channels, social systems, and the adoption process itself (Sloep et al., 2006; Freeman et al., 2007; Ngampornchai & Adams, 2016). Demographic factors (age, gender, education) also shape adoption patterns, underscoring the need for educators to tailor innovations to diverse learner profiles (Porter & Graham, 2015; Yukselturk & Top, 2012).

DOI and the UTAUT complement one another in explaining adoption. Both stress contextual factors and social influence: collaborative cultures foster innovation diffusion (Kunnari & Ilomaki, 2014), while user acceptance often hinges on peer and institutional pressures (Garone et al., 2019). Integrations with TAM further show that system quality and self-efficacy are central to adoption (Chang & Tung, 2007).

Deep and Surface Learning Approaches

The framework of deep and surface learning has shaped educational theory and practice over recent decades. Deep learning involves active engagement, intrinsic motivation, and a desire to integrate knowledge, fostering higher-order thinking, long-term retention, and meaningful application (Biggs, 1987; Lynch et al., 2012; Wang et al., 2013). In contrast, surface learning is driven by extrinsic motives, often relying on rote memorization with limited comprehension, leading to fragmented knowledge and weaker outcomes (McLaughlin & Durrant, 2016; Yang & Tsai, 2017).

Students' approaches are strongly influenced by their perceptions of the learning environment and assessment methods. Supportive and engaging contexts, along with evaluations emphasizing understanding and application, encourage deep learning, while unsupportive environments and rote-focused assessments foster surface learning (Ellis & Han, 2020; Tian, 2007). In blended settings, positive experiences with both online and face-to-face elements further promote deeper strategies and better academic results (Ellis et al., 2007).

LPA in Education

Latent profile analysis (LPA) is a latent variable modeling technique that identifies unobserved classes in a dataset by modeling response patterns on continuous indicators (Gibson, 1959; Oberski, 2016). As a person-centered approach, it delineates distinct learner subgroups, offering richer insight into educational heterogeneity than variable-centered methods and generating nuanced profiles to guide personalized interventions and instructional design.

The potential of LPA extends naturally to the ODL context, where learner heterogeneity is especially pronounced. ODL learners form a demographically diverse population with varying degrees of digital readiness, self-regulated learning (SRL) capacity, and learner autonomy (Dai et al., 2023). Learner autonomy is particularly salient in ODL settings, where learners must navigate digital environments without continuous instructor support. By applying LPA, researchers can identify subgroups sharing distinct configurations of technology acceptance, barrier perceptions, and learning strategies—providing a more nuanced foundation for adaptive and personalized course design. This aligns with advances in learning analytics that increasingly employ data-driven learner profiling to tailor instructional content and support to individual needs (Khalil et al., 2024).

Researchers have used LPA to social collaboration (Ladd et al., 2014), literacy trajectories (Foorman et al., 2016), motivation and engagement in digital contexts (Zhang & Lin, 2019; Mirriahi et al., 2018; Xu, 2024), self-regulated learning (Ning & Downing, 2014), epistemic orientations (Lonka et al., 2020), emotional profiles in medical simulations (Keskitalo & Ruokamo, 2020), and student citizenship typologies (Geboers et al., 2014). Collectively, these studies underscore motivational, emotional, and cognitive diversity in learning environments.

Beyond learners, LPA has been used to profile educators, assess barriers to technology integration (Xie et al., 2021), and evaluate teaching approaches such as flipped classrooms (Sointu et al., 2022). Its integration with methods like SEM (Teo & Milutinovic, 2015) enhances rigor, linking latent profiles with predictive pathways.

LPA advances educational research by revealing learner and educator heterogeneity, informing personalized teaching, program evaluation, and systemic improvement, and is crucial for addressing challenges in digital, blended, and traditional learning.

Taken together, the theoretical frameworks reviewed above—Diffusion of Innovations Theory, technology acceptance models, and deep–surface learning approaches—have been predominantly examined in isolation. In digital learning ecosystems, however, these dimensions are not independent: a learner's perceptions of technology usefulness and ease of use interact with internal barriers (technological self-efficacy, pedagogical beliefs), and these interactions are further shaped by the learner's habitual approach to learning—whether deep or surface. This complex interplay produces learner subgroups not visible through aggregate, variable-centered analyses. Adaptive ODL environments require an understanding of this heterogeneity in order to provide appropriate scaffolding, suitable digital tool complexity, and personalized feedback (du Plooy et al., 2024). LPA provides the methodological lens to reveal these subgroups empirically, directly justifying its application in the present study.

LPA for Deep and Surface Learners

LPA effectively categorizes students based on self-regulated learning strategies, offering insights into how deep and surface learning approaches influence academic performance. LPA gains its ability to effectively categorize individuals primarily due to its individual-centered approach and its provision of a probability-based, model-based classification framework (Moshirian Farahi & Leth-Steensen, 2023; Mammadov et al., 2016). Deep learners, driven by concept integration and comprehension, often achieve higher levels of engagement and performance than students who rely primarily on surface strategies such as rote memorization (Yonker, 2011; Quinn & Stein, 2013; Weurlander et al., 2014). However, this relationship is not deterministic, as outcomes also depend on contextual factors such as course design, assessment alignment, disciplinary conventions, and learners' prior experiences. LPA's predictive validity lies in its ability to distinguish these profiles, linking them to meaningful differences in engagement and success.

Assessment type influences how learners will approach the learning processes. Deep approaches are more easily adopted in the case of formative assessment than how summative examination case strategies are used (Nieminen et al., 2019; Weurlander et al., 2012; Elander et al., 2010). Furthermore, learners' feedback about the level of the context in which learning is done, the associated digital devices, the environment, and the activities are focused upon, tend to learn using a deep approach (Ellis & Han, 2020). Thus, LPA can elucidate learner profiles to optimize Instructional Design and Assessment in a manner that robustly and efficiently deepens learning.

METHODOLOGY

This study adopts a quantitative, cross-sectional research design employing a person-centered Latent Profile Analysis (LPA) approach. The aim is to identify latent learner profiles based on technology acceptance and perceived internal technology barriers among open and distance learners, and to examine how these profiles differ in deep and surface learning strategies.

Study Group

Participants were recruited through a convenience sampling strategy via the online student platform of Anadolu University. The study group comprises 1045 open education faculty students from Anadolu University, Turkiye. The ages of the participants ranged from 18 to 67, and the average age was 31.9 years. While 58.9% of the participants were male, 41.1% were female. 66.6% of the participants are employed, 31.3% are unemployed, and 2.1% are retired. While 47.3% of the participants have bachelor's degrees, 52.7% have associate's degrees. This profile reflects the typical sociodemographic heterogeneity of ODL learner populations in Turkiye, which serves a large and diverse adult learner base (Yukselturk & Top, 2012)

Data Collection Tools

To address the research questions, a series of validated measurement tools were employed. These instruments were selected for their relevance to assessing learners' approaches, perceptions of technology acceptance, and internal barriers to technology integration. Each tool is briefly described below, together with information on its structure, reliability, and adaptation for the present study.

Learning Approach Scale

The study employed the Revised Two-Factor Study Process Questionnaire, which was first created by Biggs et al. (2001) and subsequently adapted into Turkish by Besoluk and Onder (2010). The questionnaire consists of 20 items rated on a five-point Likert scale, with response options ranging from "never" to "always." Ten items assess the Deep Learning (DL) approach, while the remaining ten assess the Surface Learning (SL) approach. Sample items include "I test myself until I fully understand important subjects" for the DL subscale and "I think it is unnecessary to learn subjects that are unlikely to be covered in the examinations" for the SL subscale. In the current sample (n = 1,045), the DL subscale demonstrated acceptable internal consistency, with a Cronbach's alpha coefficient of .787 and a McDonald's omega coefficient of .976. The SL subscale also showed satisfactory reliability, with Cronbach's alpha and McDonald's omega coefficients of .812 and .813, respectively. For the overall scale, Cronbach's alpha was .866 and McDonald's omega was .871, indicating good internal consistency. As the instrument is an established and previously validated measure and the present study did not involve scale development or adaptation, an additional confirmatory factor analysis was not conducted.

Technology Acceptance and Usage Integrated Scale

Consistent with our learning-analytics framing, the following psychometric instruments—including the Technology Acceptance and Usage Integrated Scale—were used primarily as analytical tools to model learner characteristics rather than merely as data-collection questionnaires. The original technology acceptance and usage integrated model-2 (UTAUT-2) is a 7-Point Likert scale with 28 items that was created by Venkatesh et al. (2012) and modified by Yilmaz and Kavanoz (2017). The scale has 8 sub-dimensions (performance expectancy, hedonic motivation, effort expectancy, social influence, facilitating condition, behavioral intention, price value, habit). After validation studies, there were 27 components in the model. In the present sample (n=1,045), fit indices for the tested model (X^2=2054.800, p=0.000, df=722, normed fit index=0.868; standardized root mean square residual (SRMR)= 0.04) are within acceptable ranges. It is seen that Cronbach alpha values vary between .76 and .93 for subscales and .97 for the entire scale, based on the current sample.

Perceived Internal Technology Barriers Scale

Developed by Basarmak & Hamutoglu (2020), the Perceived Barriers in Technology Integration (PITB) measure comprises 51 items and has a 14-factor structure. According to Hamutoglu (2021), the perceived internal technological barriers dimension consists of six subdimensions: assessment (ASSES), family resistance (FR), technological self-efficacy beliefs (TSEB), pedagogical self-efficacy beliefs (PSEB), beliefs in learning–teaching activities (BLTA), and beliefs in expert support (BES). The confirmatory factor analysis results reported for the original validation of the measure indicated an acceptable model fit (χ^2/df = 1.597, CFI = .92, IFI = .92, GFI = .88, AGFI = .86, RMSEA = .03, and SRMR = .04). In the current sample (n = 1,045), the perceived internal technological barriers scale comprised 30 items distributed across these six subdimensions. The calculated CFA fit indices for internal technological barriers scale shows an acceptable model fit (X^2/df=3.56, CFI=0.99, IFI=0.99, GFI=0.99, AGFI=0.98, RMSEA=0.05, SRMR=0.01). The Cronbach's alpha coefficients were .873 for BLTA, .912 for BES, .902 for TSEB, .854 for PSEB, .880 for FR, and .766 for ASSES. The Cronbach's alpha coefficient for the overall 30-item scale was .851. Thus, all subscales and the total scale demonstrated acceptable internal consistency, as their coefficients exceeded the commonly accepted threshold of .70 (Buyukozturk, 2020). Perceived internal technological barriers were operationalized as a composite latent construct based on the scores obtained from the six subdimensions.

The perceived internal barriers appear to be a latent variable based on the sum of the subdimensions' scores. The statement "*I believe that the use of technology in learning-teaching activities increases learning*" is an example of one of the four items that make up BLTA. One of the nine items that make up BES is "I believe that referring to expert support when using technology makes it easier for me."

Additionally, PSEB and FR subdimensions have five items, whereas TSEB has four. For instance, *"I feel myself lacking in the use of technology in courses (TSEB),"* *"I pay regard to the characteristics of the target group when using technology in courses (PSEB),"* and *"Families do not insist on the use of new technologies (FR)"* are examples of PSEB and FR subdimensions.

Lastly, there are three elements that make up the ASSES sub dimension. An example item that defines this component is "Use of technology at schools serves the assessment process rather than the teaching process."

Data Analysis

Prior to analysis, data screening was conducted to inspect univariate distributions and identify potential outliers. For missing data, listwise deletion was preferred. In addition, rather than normality, Variance Inflation Factor (VIF) scores were calculated to detect potential multicollinearity among the Latent Profile Analysis (LPA) variables. The resulting VIF value of 1.00 indicates the absence of multicollinearity issues within the model. In LPA, model selection is performed after the data preparation phase; Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) are used in the model selection phase, and after model selection, model parameters and groups are estimated (Olivera-Aguilar & Rikoon, 2017). In this context, the analyses made via the R program with the use of TidyLPA and Mclust packages (Rosenberg et al., 2018) demonstrated that the EEI model defines the best profile memberships.

FINDINGS

This section presents the results of the analyses conducted to explore the latent profiles of open and distance learners with respect to their learning approaches, technology acceptance, and perceived barriers. The findings are organized to first provide descriptive statistics of the key variables, followed by model selection outcomes from latent profile analysis, and finally comparisons of the identified profiles in terms of deep and surface learning strategies. Table 1 shows the descriptive statistics values of the scores obtained by the research participants from the PITB and UTAUT-2 scales.

Table 1. Descriptive statistics of PITB and UTAUT

	N	Mean	SD	Min	Median	Max
Total_PITB	1045	120,19	26,17	44	118	161
Total_UTAUT-2	1045	78,61	12,40	33	81	108

The mean of the scores obtained from the PITB scale is 120.19 points (Minimum 44, Maximum 161) and the standard deviation is 26.17. The mean of the scores obtained from the UTAUT-2 scale is 78.61 points (Minimum 33, Maximum 108) with a standard deviation of 12.40 points. After the descriptive statistics, BIC analyses were performed in order to decide on the model to be used in the LPA analysis. As a result of BIC analyses, it was determined that the best working model was the EEI model (model 3). In the EEI model, the covariances are fixed to zero and the variance is equally constrained to perform the classification process (Wardenaar, 2021).

Figure 1 and Table 2 show the different statistics used in class selection for the EEI model.

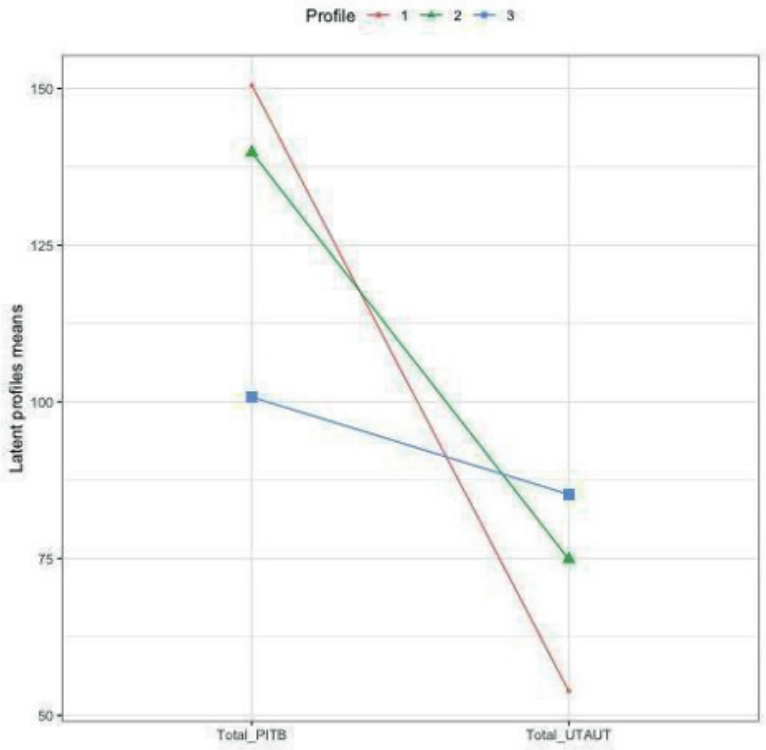


Figure 1. Comparison of fit indices EEI model

When Figure 2 scree plot is examined, there is an increase in some fit indices in the 4-class model after the 3-class model.

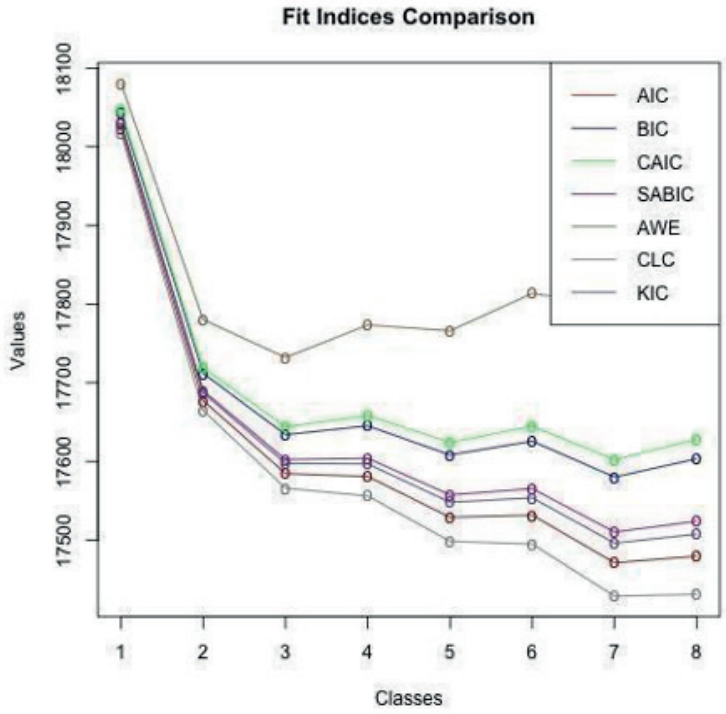


Figure 2. Arithmetic Averages of Classes For EEI 3-Class Solution

When Table 2 is examined, there is an increase in the ICL fit index after the 3-class model. When the class sizes in Table 2 are examined, it is seen that the class sizes decreased below 5% after the 3-class model.

Table 2. Model Fit Statistics for Determining the Optimal Number of Classes

Model	BIC	BLRT (p)	Class assignment probability (class size)	Entropy
1 class	-9.007,57	-	-	-
2 classes	-8.831,65	351.85 (0.001)	457 (%44)/588 (%56)	0,73
3 classes	**-8.782,26**	**98.78 (0.001)**	**71 (%7)/423 (%40)/ 551 (%53)**	**0,74**
4 classes	-8.777,45	9.62 (0.009)	47 (%4)/401 (%38)/223 (%21)/374 (%36)	0,60
5 classes	-8.748,54	57.81 (0.001)	109 (%10)/131 (%13)/478 (%46)/39 (%4)/288 (%28)	0,74
6 classes	-8.746,86	3.37 (0.083)	108 (%10)/137 (%13)/283 (%27)/34 (%3)/192 (%18)/291 (%28)	0,62
7 classes	-8.713,61	66.49 (0.001)	63 (%6)/225 (%22)/203 (%19)/93 (%9)/292 (%28)/44 (%4)/125 (%12)	0,79
8 classes	-8.714,79	-2.36 (1)	75 (%7)/212 (%20)/139 (%13)/98 (%9)/304 (%29)/43 (%4)/131 (%13)/43 (%4)	0,72

Note: BIC: Bayesian Information Criteria, BLRT: The bootstrap likelihood ratio test. Bold type indicates the selected best-fit model.

When the values in Figure 1 and Table 2 are analyzed, it can be concluded that the 3-class solution is the best working model for the EEI model, and the LMR analysis in Table 2 also confirms that this choice is appropriate.

The EEI 3-class solution categorized the groups as Class 1 (*preservers*), Class 2 (*prudents*), and Class 3 (*pioneers*). Analysis of the arithmetic means revealed that Class 1 barriers were perceived as elevated with reduced acceptance scores, while Class 2 barriers exhibited moderate acceptability. In contrast, Class 3 barriers demonstrated poor acceptance despite high approval.

After determining the optimal number of the latent profiles, a one-way ANOVA was utilized to compare the profiles regarding deep learner and surface learner. As seen in Table 3, there were significant differences between the latent profiles in the deep learner ($F(2,1042) = 97.468$, $p<.05$, $\eta^2 = .158$). Post hoc comparison using the Bonferroni test indicated significant differences among profiles in deep learners. Those classified in Profile 1 attained the highest technology adoption scores compared to others. Accordingly, it is seen that the significant differences were among Profile 1 (*preservers*; X = 40.028), Profile 2 (*prudents*; X = 32.143) and Profile 3 (*pioneers*; X = 32.143), and Profile 2 and Profile 3 in favor of preversers and prudents (all $p < .001$).

Table 3. Analysis of Variance across Latent Profiles

	Profile 1 (preservers) (n=71)		Profile 2 (prudents) (n=422)		Profile 3 (pioneers) (n=552)		F(2,1042)	Mean Differences	η^2
Variables		SS		SS		SS			
Deep learner	40.028	5.425	36.533	6.169	32.143	5.906	97.468***	1***-2 1***-3 2***-3	0.158
Surface learner	28.169	7.311	30.867	7.755	29.667	5.540	6.960**	1-2** 2*-3	0.013

*Note: ***p<.001; **p<.01; *p<.05*

Since homogeneity of variance was not ensured for surface learner data, Brown-Forsythe test was performed and it was found that there was a significant difference between the latent profiles in surface learner (Brown-Forsythe F (2, 257.909) = 6.132, p < .01, η^2=.013). Post hoc comparison using Games Howell test showed that there were significant differences between Profile 1 and Profile 2; and Profile 2 and Profile 3 in surface learners. Accordingly, it is seen that the significant differences were between Profile 1 (*preservers*; X = 28.169) and Profile 2 (*prudents*; X = 30.867) (p < .01); Profile 2 (*prudents*; X = 30.867) (p<.05) and Profile 3 (*pioneers*; X = 29.667), in favor of prudents. No significant difference was observed between Profile 1 and Profile 3.

DISCUSSION

The learner profiles—pioneers, prudents, and preservers—correspond to Rogers' (1995) categories: pioneers (innovators/early adopters) legitimize innovation; prudents (early majority) adopt once benefits are demonstrated; preservers (late majority/laggards) adopt only under pressure. Within the ODL context, this categorization carries specific pedagogical significance. Preservers are not simply reluctant learners; rather, their profile—high perceived internal barriers alongside lower technology acceptance—suggests that the conditions within their digital learning environment have not yet sufficiently reduced the cognitive and affective costs of technology engagement. This may include poorly designed interfaces, lack of adequate technical support, or a mismatch between instructional design and their existing digital skill repertoire. Prudents represent a pragmatic equilibrium: once the utility of digital tools has been demonstrated and socially legitimized—consistent with the observability and relative advantage attributes of DOI Theory (Rogers, 1995)—they adopt purposefully and efficiently. Pioneers exhibit high technology acceptance but do not systematically score highest on deep learning, suggesting a meaningful dissociation between enthusiasm for digital innovation and the sustained cognitive engagement that deep learning requires. Deep learners, intrinsically motivated to integrate and contextualize knowledge, typically coincide with pioneers (Biggs, 1987), whereas surface learners, driven by external demands and relying on rote, fragmented study, align with prudents and preservers (McLaughlin & Durrant, 2016). This alignment supports conceptualizing learner groups as pioneers, prudents, and preservers in technology adoption.

By linking deep and surface learning approaches with these adoption profiles, LPA underscores the importance of tailoring ODL environments. Designing with these variations in mind enhances adaptability, personalization, and inclusivity, ultimately fostering more engaging and effective learning experiences.

The Variations Learning Profiles Explored among Deep and Surface Learners

The distinction between deep and surface learners across the proposed profiles—pioneers, prudents, and preservers—offers valuable insights into technology adoption in open and distance learning (ODL). First of all, findings indicate that prudents demonstrate higher adoption than preservers regardless of learning style, while pioneers show the strongest adoption among deep learners (see Figure 3). Pioneers, akin to early adopters, are driven by curiosity and anticipated benefits, whereas prudents (early majority) are influenced by relative advantage, compatibility, and peer experiences. Preservers, representing laggards, tend to adhere to traditional practices and adopt new methods only when necessary, often lagging behind their peers (Doo et al., 2019; Porter & Graham, 2015; Cakiroglu et al., 2022; Konsky & Oliver, 2012).

Results for deep and surface learning styles were significant (Table 3). Among the latent profiles (pioneers, prudents, and preservers), deep learners in the preserver profile scored significantly higher than prudents and pioneers, whereas differences between prudents and pioneers favored prudents. This unexpected finding warrants theoretical explanation. One interpretation draws on psychological reactance theory (Guo, 2024; Miron & Brehm, 2006): learners with deep learning orientations who perceive technology as externally imposed or pedagogically misaligned may resist digital tools not because of deficient motivation, but because they experience those tools as incompatible with their preferred, internalized approach to learning. This interpretation aligns with Xie et al.'s (2021) finding that internal barriers—particularly technological self-efficacy beliefs—exert a stronger influence on technology integration behavior than external barriers. From a self-regulated learning (SRL) perspective, preserver deep learners may demonstrate high metacognitive regulation of their content engagement while exercising relatively low regulatory control over their technology

use (Hromalik & Koszalka, 2018; Yot-Dominguez & Marcelo, 2017). The SRL framework implies that targeted scaffolding of technology-related self-regulation strategies—distinct from content learning strategies—may be the most effective intervention for this group. This insight has direct implications for instructional design in ODL: deep learning orientation and technology acceptance should not be assumed to be correlated, and ODL course designs must address each dimension independently. For surface learners, significant differences between profiles also favored prudents. Deep learning strategies—linked to higher-order thinking, synthesis, and application—align with the behaviors of pioneers, who experiment with new technologies and materials (Newton & McCunn, 2015; Chen et al., 2023). In contrast, surface learners, who rely on rote memorization, are often correlated with late adopters and preservers, showing reluctance toward innovative methods (Akyol & Garrison, 2011; McLaughlin & Durrant, 2016). Assessment practices play a key role: evaluations focused on comprehension and application encourage deep learning, while rote-based tests foster surface learning (Tian, 2007).

Pioneers in ODL are more likely to adopt deep learning when they perceive their environment as engaging, whereas surface learners tend to pursue minimal outcomes, reinforcing slow adoption patterns. This study investigates technology adoption through LPA by utilizing the perceived internal barriers and technology acceptance with the basis of UTAUT-2 scales. Accordingly, the explored latent profiles were named in line with Rogers' (1995) diffusion attributes—specifically relative advantage, compatibility, and complexity— to maintain theoretical consistency with innovation adoption profiles (pioneers, prudents, preservers). These adoption factors strongly shape learner attitudes. Research confirms that learners' intentions to engage with e-learning are significantly predicted by these perceptions (Sahin et al., 2022; Hsu & Lin, 2021). Thus, designing ODL environments that enhance perceived utility, reduce barriers, and support motivation is essential for fostering adoption across all learner profiles.

CONCLUSION

This study examines how digital learning ecosystems can be designed for adaptable, effective, and personalized instruction that promotes engaging, inclusive learning. Using latent profile analysis of technology acceptance and perceived intrinsic technology barriers among open and distance learners, we identified three profiles: *preservers* (high barriers, low acceptance), *prudents* (moderate barriers and acceptance), and *pioneers* (low barriers, high acceptance). Furthermore, these obtained latent profiles were investigated in terms of deep and surface learners. The distinction between deep and surface learners within the suggested latent profiles—pioneers, prudents, and preservers—provides significant insights into technology adoption in open and distant learning (ODL). The findings on deep and surface learning are noteworthy when examined across learner profiles. Among deep learners, preservers and prudents—despite being characterized as more resistant to technology—display higher levels of technology adoption than pioneers. Thus, within deep learning strategies, profiles ostensibly less receptive to innovation show greater adoption than those labelled more pioneering. Among surface learners, prudents also exhibit comparatively higher technology adoption. These results challenge the assumption that students employing deep learning are necessarily more open to innovation.

The findings indicate that, contrary to expectations, prudents rather than pioneers adopt technology most efficiently in digital learning environments. Deep learning alone does not ensure technology acceptance; some deep learners actively resist innovations that are not internalized or pedagogically mediated. Effective technology integration therefore depends on learners' cognitive styles, pedagogical context, trust in the technology, and deliberate alignment of tools with instructional goals. Deep learning may reflect a desire for control, cognitive consistency, and pedagogical coherence, leading some deep learners to experience poorly integrated technologies as distractions rather than supports for meaningful learning. Among surface learners, a similar pattern favors prudents, underscoring that evaluations of technology adoption must consider not only learning approaches but also learners' risk tolerance, openness to innovation, and expectations for structured learning.

RECOMMENDATIONS, LIMITATIONS, AND PRACTICAL IMPLICATIONS

Recommendations

ODL institutions should deploy adaptive digital tools aligned with learner profiles (preservers, prudents, pioneers). Preservers require user-friendly platforms and digital literacy support, whereas pioneers benefit from advanced interactive tools. Targeted interventions (e.g., training, workshops, motivational modules) can foster deep learning strategies and enhance technology acceptance, particularly among preservers and prudents. Continuous feedback mechanisms and adaptive platform features are essential for responding to evolving learner needs.

Limitations

This study focuses on ODL, limiting applicability to traditional face-to-face education. Data were largely self-reported, raising concerns about accuracy. Critically, the learner profiles identified here—preservers, prudents, and pioneers—should be understood as dynamic rather than fixed. Technology exposure, instructional interventions, and changes in the digital learning environment can shift individual learners between profiles over time, consistent with Rogers' (1995) observation that late adopters eventually integrate innovations as social and structural barriers diminish. This cross-sectional design captures a single temporal snapshot and cannot model such trajectories. Future research should employ longitudinal or experience-sampling designs to track profile transitions and assess the causal impact of targeted interventions on profile mobility. Additionally, the sample was drawn exclusively from Anadolu University in Turkiye. While this institution represents one of the world's largest open universities by enrollment and its learner population reflects broad sociodemographic diversity, the findings may not generalize to ODL contexts characterized by different technological infrastructure, cultural orientations toward technology, or instructional design traditions. Multi-institutional and cross-national replications are encouraged. Moreover, external factors such as socioeconomic status, prior technological experience, and cultural context were not fully addressed. While the 3P model (preservers, prudents, pioneers) is useful, it may overlook dimensions such as emotional engagement, social presence, and collaboration.

Practical Implications

The three learner profiles identified in this study provide an empirical foundation for adaptive, personalized, and inclusive ODL design. Profile-specific recommendations are as follows:

For preservers: ODL institutions should offer scaffolded onboarding sequences that progressively build technological self-efficacy through low-stakes tasks (e.g., short interactive videos, brief auto-graded quizzes). AI-driven chatbots can provide immediate, non-judgmental support for technology navigation difficulties, reducing the anxiety associated with unfamiliar interfaces. Peer mentoring programs that pair preservers with prudent learners—who have already pragmatically internalized technology utility—leverage the social influence dimension of UTAUT-2 to reduce psychological barriers at low institutional cost.

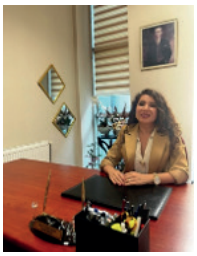
For prudents: Course designs should incorporate social-proof mechanisms—peer success dashboards, collaborative annotation tools, discussion forums with visible participation metrics—that render the benefits of technology use observable and legitimate, directly activating the observability attribute of Diffusion of Innovations Theory. Adaptive content sequencing systems can identify the pace at which prudents are ready to engage with increasingly complex tools and adjust delivery accordingly.

For pioneers: Advanced digital features—open-ended project environments, AI-generated feedback on drafts, knowledge-building wikis, and creative digital production tasks—sustain engagement and match high technology acceptance with deep learning demands. Course designers should avoid calibrating the default difficulty and tool complexity of ODL courses exclusively for pioneer learners, as this marginalizes prudent and preserver populations.

At the institutional level, LPA-derived learner profiles can be operationalized within learning analytics dashboards. Early in a course, brief diagnostic surveys or behavioral trace data (e.g., login frequency, tool engagement patterns) can be used to assign probable profile membership and automatically trigger

differentiated support protocols. AI-supported recommendation engines can then personalize content complexity, tool type, and feedback intensity by profile, offering a scalable and evidence-based pathway toward genuinely inclusive ODL ecosystems. Scalable interventions such as MOOCs should embed adaptive learning strategies that foster deep learning. Evaluation frameworks must encompass adaptability and technology engagement to support continuous improvement of digital ecosystems.

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