Towards tailored online learning: Predicting learner profiles in an online learning environment with perceived needs satisfaction

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ABSTRACT: This study examined the relationship of learner profiles and the satisfaction of basic psychological needs among 109 undergraduate physics students participating in an online algebra training program. The study utilized latent profile analysis to identify groups of learner profiles and explored the role of students' perceived needs satisfaction in predicting group composition using multinomial logistic regression. The results indicated that not all students benefited equally from the online training program. Four distinct groups of learner profiles emerged from the analysis: high achiever-high engagement, high achiever-medium engagement, low achiever-high engagement, and low achiever-low engagement. There were significant differences in perceived autonomy and competence among these groups, with students' perceived autonomy and competence predicting the group composition. The study suggests the importance of considering motivational factors such as students' perceived needs satisfaction when designing tailored online learning experiences.

Keywords: online learning, perceived needs satisfaction, adaptive learning, latent profile analysis

1. Introduction

Over the past few decades, online learning has emerged as a popular and promising channel for education, transforming the way learners acquire knowledge and skills. Although the accessibility and convenience offered by online learning environments have made education more inclusive and flexible than ever before, online learning has experienced challenges such as high dropout rates and decreased motivation (Bağrıacık Yılmaz & Karataş, 2022; Mamolo, 2022). It has become increasingly evident that students exhibit diverse learning behaviors and patterns in online learning environments and a one-size-fits-all approach to online instruction is inadequate in addressing the diverse needs of students, and there is a need to tailor online learning experiences to individual learners by developing individualized instructional approaches or adaptive online environments (El-Sabagh, 2021; Wan & Yu, 2023).

Currently, learner models in adaptive online learning environments are primarily based on factors such as learners' knowledge levels and learning styles, with limited consideration of other influencing factors (Talaghzi et al., 2020). Identifying key factors that influence learner behaviors and performance in online learning settings is crucial for developing more effective adaptive online learning environments tailored to individual learners. Aligned with this research agenda, this study aims to examine the relationship between students' online learning behaviors and the motivation-related factor of basic psychological needs satisfaction. According to Self-Determination Theory (SDT), perceived basic psychological needs satisfaction in autonomy, competence, and relatedness can significantly affect students' intrinsic motivation and engagement in learning activities (Ryan & Deci, 2017). As a result, it is important to examine whether students' perceived needs satisfaction can predict the formation of learner groups based on their online learning behaviors and potentially be considered as a variable to improve learner models for adaptive online learning environments. In this study, the researcher first used latent profile analysis to identify distinct groups of learners. Then, multinomial logistic regression was conducted to find out how well students' perceived needs satisfaction predicts their membership in these groups.

1.1. Research on learner profiles in online learning environments

Learner profiling involves using data about learners to categorize them into groups based on their characteristics, behaviors, or other attributes (Alexander & Murphy, 1998). While various studies have explored learner profiles in online learning environments, they often focus on specific behaviors or characteristics without integrating a motivational perspective, which may limit the depth of understanding regarding learner engagement and success. For example, Yoon et al. (2021) classified students into active and passive learners based on behavioral patterns in video-based online learning, finding that active learners had higher achievement. However, this study did not consider the underlying motivational factors that might differentiate active learners from passive ones. Similarly, Çebi and Güyer (2020) identified three profiles based on student interaction patterns with learning materials: "Less use students", "Video, Example, Forum intensive use students", and "Tutorial, Exercise, Concept Map intensive use students". Across these groups, they found significant differences in terms of learning performance, task value, self-efficacy, and sub-dimensions of self-regulated learning (SRL) strategies. But they did not account for how students' motivations might influence their engagement with different types of resources and learning performance.

Some studies examined online learners' self-regulated learning (SRL) profiles. For instance, Maldonado-Mahauad and the colleagues (2018) identified three distinct clusters of learners: comprehensive learners, targeting learners, and sampling learners based on six different interaction sequence patterns associated SRL strategies. In the study conducted by Araka and the colleagues (2022), four distinct SRL profiles were identified: poor self-regulators, intermediate self-regulators, good self-regulators, and exemplary self-regulators. Their research uncovered a significant relationship between these SRL profiles and students' learning, but the role of motivational factors in these profiles was not fully explored.

Other researchers attempted to identify learner profiles based on students' individual characteristics. Maaliw et al. (2022), for example, classified students into High Grit and Low Grit groups using system data and revealed that grit had a weak connection with course grades but displayed a strong positive relationship with professional achievement as measured by salary. They, however, did not examine how motivational factors might interact with these traits to influence learning outcomes. An exception is the study conducted by Yu et al. (2022). The researchers not only identified four learner profiles based on whether students had low, average, above average, or high emotional self-efficacy, but also found student self-regulation strategies and their motivation in terms of identified regulation and external regulation significantly predicted profile membership.

In a few cases, the identified learner profiles are utilized to enhance the adaptive capabilities of online learning environments. For instance, Moubayed and the colleagues (2020) analyzed the log data from the learning management system and classified students into three different engagement levels to effectively identify students in need of assistance. Peng and Fu (2022) constructed a learning pattern recognition model that incorporated individual learning behavior characteristics to improve the satisfaction of personalized learning resource recommendations in an online learning environment. However, these studies also lack consideration of motivational factors, which could potentially enhance the predictive power of the existing models.

In sum, all these studies contribute to the understanding of student online learning behaviors and the underlying factors that influences these behaviors. However, the literature suggests a critical oversight – the limited examination of motivational factors as variables in understanding learner profiles. In particular, perceived needs satisfaction, given its fundamental role in intrinsic motivation, could significantly influence how students engage with online learning. As a result, this study aims to fill this gap by examining learner profiles through the lens of self-determination theory (SDT) and offering deeper insights into the motivational dynamics that drive different types of learners. The insights gained from this study may potentially enhance the design of adaptive systems that aim to provide more tailored support and interventions to meet the diverse needs of learners.

1.2. SDT and online learning

SDT is a highly influential model in behavioral science and is widely regarded as one of the most comprehensive and practical motivation theories in social sciences (Proulx et al., 2017). Built on the belief that all individuals have inherent inclinations to develop an increasingly complex and unified sense of self, SDT posits that satisfying three basic psychological needs, namely autonomy, competence, and relatedness, is necessary for the growth and overall wellness of human beings (Deci & Ryan, 2004). Autonomy refers to the feeling of being in control of one's actions and behaviors. Competence is the sense of being capable and successful in the way one interacts with their surroundings and being able to take the opportunities to demonstrate their abilities. Relatedness is the need to engage with and establish meaningful relationships with others (Deci & Ryan, 2004). The satisfaction or negligence of these basic psychological needs can facilitate or forestall autonomous types of motivation, which affect individual's emotions, creativity, engagement, persistence, and performance (Ryan & Moller, 2016; Vansteenkiste & Ryan, 2013). It is important to note, however, that it is not the event but the functional significance of the event, that is, the individual's interpretation of the event, that has an effect on intrinsic motivation (Ryan & Deci, 2017). As a result, an online learning environment can be perceived as either controlling or supportive by different individuals based on their own characteristics.

Using SDT as a framework, researchers have examined the relationship of student perceived need satisfaction, motivation, and performance in online learning environments. Chen and Jang (2010) found that student reported contextual support for autonomy and competence in the online courses positively predicted student perceived needs satisfaction, which, in turn, positively predicted student motivation, time spent on studying, and the number of times that students accessed the online content pages. Hsu et al. (2019), by further examining the SDT-based model in an online learning context, found perceived needs satisfaction mediated the relationship between contextual support for autonomy and self-determined motivation, which significantly predicted learning gains, course grade, and perceived knowledge transfer. The findings were echoed by many other researchers, who found that students' perceived needs satisfaction positively affected their motivation (Filak & Nicolini, 2018; Mendoza et al., 2023), level of engagement (Chiu, 2022, 2023), and learning outcomes (Hsu et al., 2019; Salikhova et al., 2020; Wang et al., 2019).

Given the positive effects associated with perceived needs satisfaction, exploring the connection between learner profiles in online learning environments and perceived needs satisfaction is crucial, as it can enhance our understanding of the mechanisms that underlie student motivation, engagement, and learning in online environments. So far, there has been little research exploring this connection. Therefore, the current study aims to address this gap and examine students' online learning profiles and their relationship with perceived needs satisfaction. There are three research questions:

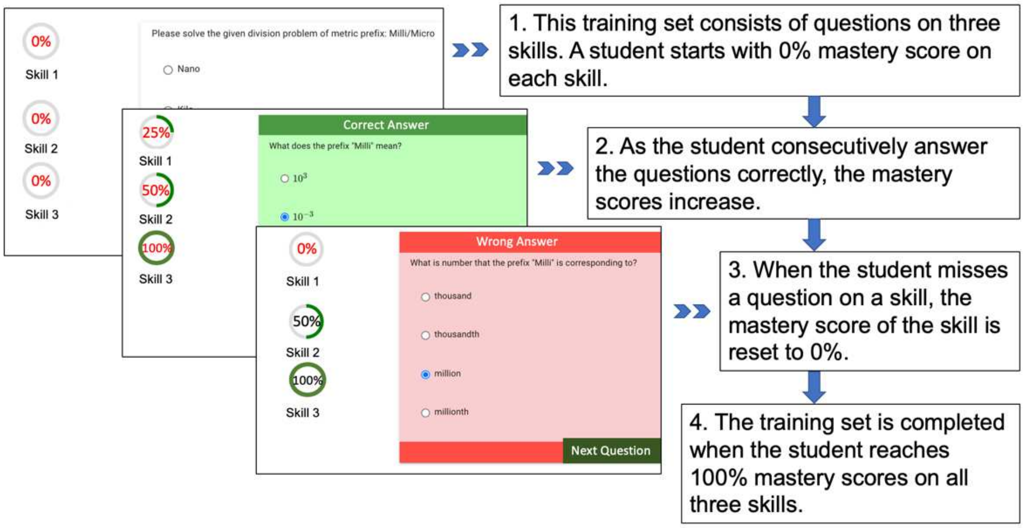
(1) How many distinct groups of learner profiles can be identified from students who participated in the online training program? What are the characteristics of each group?
(2) Are there variations in students' perceived needs satisfaction levels among these different groups?
(3) To what degree does students' perceived needs satisfaction predict student membership in these groups?

2. Method

2.1. An online training program

The study was conducted using an online training system developed by Mikula and Heckler (2017). Based on research-validated principles and methods (Mikula & Heckler, 2017), the online training system was developed to enhance student mastery of basic skills in STEM (Science, Technology, Engineering, and Mathematics) through explicit practice. Figure 1 shows how STEM Fluency (SF) system works. Students typically work on the assignments in SF after class for 15-20 minutes every week for several weeks to build the mastery of a set of skills. Although research has shown positive effects of using this online training system in enhancing student performance on essential skills (Nieberding & Heckler, 2023), how students have behaved differently and benefitted differently from the online training have not been thoroughly studied.

Figure 1. How STEM Fluency works



2.2. Participants and procedures

Participants were 109 undergraduate students enrolled in an online asynchronous algebra-based physics course, the majority of whom are non-physics science or technology majors. Among all students, 57.8% are female and 42.2% are male. None of the students have used the STEM Fluency system prior to the study. At the beginning of the semester, students received brief instructions on how to get registered in the STEM Fluency system, how to participate in the online training, and why it is important to practice the algebra skills in the system.
Starting from week one, all students participated in a five-week online training to improve their mastery of a set of algebra skills that are essential for students to perform the physics calculations and problem-solving required in this course. Students took the pre-test before the training started. Each week, students were assigned to complete the practice focused on a subset of the skills. The mastery count was set to three, meaning, in a practice session, students had to answer three questions of a skill consecutively correctly to achieve mastery of the skill. As explained in Figure 1, if students failed to answer one question correctly during the process, the mastery score was set back to 0%, and they will have to work on additional questions on this skill until they achieved 100% mastery score. To encourage students' participation in the training, they received 5% their course grade for completing all the five-week training, but they were not required to achieve mastery of these skills. The grade credit served as an external motivator for students to participate in the training. According to our previous study, when the incentive was provided, the majority, though not all, of the students were able to complete the training (Gao et al., 2021). At the end of the fifth week, post-test was administered to measure student mastery of the skills. Students also took a survey measuring their perceived needs satisfaction while they were participating in this online training.

2.3. Data collection

2.3.1. Student learning

To assess student learning, a pre-test and post-test were administered at the beginning of the semester and at the end of the five-week training respectively. Both tests consisted of an identical set of 20 multiple-choice questions to measure student mastery of the skills covered during the training. The questions were carefully constructed by the course instructor to ensure that they accurately measure student performance in these skills.

2.3.2. Student behavior

The online training system automatically records trace data that indicate a student's learning behavior. For each student, four types of trace data were retrieved from the system: total number of questions attempted, total number of questions answered correctly, total time spent on task, and total number of times a student achieved mastery for a skill. In addition, since not all students reached 100% mastery scores for every skill due to varying levels of practice, the mastery rate for each student was calculated by dividing the number of times the skills were mastered by the number of times that the skills were practiced.

2.3.3. Student needs satisfaction

A survey was used to collect information on students' perceived needs satisfaction in autonomy, competence, and relatedness during the online training. The survey consists of subscales based on the Basic Psychological Needs Satisfaction and Frustration Scale (BPNSFS) (Chen et al., 2015), which has been validated (Rodrigues et al., 2019; Šakan, 2022) and widely used to measure subjects' satisfaction and frustration with the three basic psychological needs when engaged in activities such as online learning (Carmignola et al., 2021; Schürmann & Quaiser-Pohl, 2022). More specifically, three subscales measuring needs satisfaction were adopted in this survey, and within each subscale, there were four questions asking students to rate their perceived autonomy, competency, and relatedness satisfaction respectively. Here are some example questions: "When completing the training in STEM Fluency system, I felt a sense of freedom and choice during the practice." (Autonomy Satisfaction), "When completing the training in STEM Fluency system, I felt competent when solving the problems." (Competence Satisfaction), and "When completing the training in STEM Fluency system, I felt close to the other participants." (Relatedness Satisfaction). Students were instructed to evaluate each statement on a scale of 1 to 7, where 1 indicates "not true at all" and 7 represents "very true". For each student, scores in perceived autonomy satisfaction, competency satisfaction, and relatedness satisfaction were calculated using the mean scores for each respective subscale.

2.3.4. Student learning experiences

To better understand the research findings, the researcher decided to collect additional follow-up interview data on student learning experiences. After the five-week training, the researcher reached out to the whole class via email asking for volunteers to participate in the interview. Eleven students responded and participated in the interviews. Example interview questions included: "Do you feel the training helps with your studies in the course?"; "What motivated you to work on the training problems?"; and "Do you think the design of the system is user-friendly? Why or why not?"

2.4. Data analysis

Out of the 109 students, one student who did not participate in any of the online training sessions was excluded from the data analysis. Subsequently, box plots were employed to visualize the remaining dataset and identify outliers. Four data points with unusually large values for total time on task were removed, resulting in a final dataset of 104 students for the analysis. In this study, the statistical analyses were conducted using R software, an open-source programming language and software environment specifically designed for statistical computing and graphics.

While the study's primary focus does not center on evaluating the online training program's effectiveness, a paired sample t-test using students' pre-test and post-test scores was conducted to offer valuable contextual information on student learning. Then, to address the first research question, latent profile analysis was conducted. Latent profile analysis (LPA) refers to techniques aimed at uncovering latent groups in data by assessing the likelihood of individuals belonging to various groups (Masyn, 2013). LPA has been widely used in the field of education to identify subgroups of students with different individual characteristics, motivational profiles, learning behaviors, and learning needs (e.g., Hong et al., 2020; Miller et al., 2021; Sun & Xie, 2020; van Alten et al., 2021). In this study, LPA was conducted to identify learner profiles using six measures associated with students' performance and behaviors: pre-test score, post-test score, total number of questions attempted, total number of questions answered correctly, total time spent on task, and mastery rate. While larger sample sizes are generally preferred for LPA to ensure stable and reliable profiles, there is precedent in the literature for conducting LPA with smaller samples. For example, studies by Sun and Xie (2020) with a sample size of 104 and van Alten et al. (2021) with a sample size of 150 have successfully employed LPA with sample sizes comparable to ours. These studies have demonstrated that meaningful and interpretable profiles can be derived with sample sizes in the range of 100-150 participants.

To conduct the LPA, '*mclust'* package in R was used. '*mclust*' is a R package for model-based clustering, classification, and density estimation based on Gaussian finite mixture models, including Bayesian regularization, dimension reduction for visualization, and resampling-based inference. To ensure the robustness of the findings, a number of commonly used model fit measures were calculated and compared against each other to determine the best model. These include Bayesian information criterion (BIC; Schwarz, 1978), integrated complete-data likelihood (ICL; Biernacki et al., 2000; 2010), approximate weight of evidence criterion (AWE; Banfield & Raftery, 1993), and consistent Akaike's information criterion (CAIC; Bozdogan, 1987). The bootstrap likelihood ratio test (BLRT; McLachlan & Peel, 2000) was also used to evaluate the fit of a model in comparison with a model with one less profile. The consistency of the findings across these checks will suggest that the results are reliable despite the sample size.

To address the second research question regarding potential differences in student perceived needs satisfaction across the LPA-derived groups, one-way MANOVA tests were conducted. The dependent variables in this analysis were the perceived autonomy, competence, and relatedness scores, while the independent variable was the cluster membership. For the third research question, examining whether student perceived needs satisfaction could predict student membership in these groups, a multinomial logistic regression was performed. In this analysis, the dependent variable consisted of the clusters derived from LPA, and the predictors were student perceived autonomy, competency, and relatedness scores. Finally, data collected from the interviews were reviewed to identify information that could shed light on the findings.

3. Results

3.1. Student learning

As stated previously in the Data Analysis section, a paired-sample t-test was conducted to provide essential contextual information on student learning. The result indicated that students' post-test scores (M = 10.79, SD = 3.50) were significantly higher than their pre-test scores (M = 8.23, SD = 2.76), t = 9.73, p < .001. This suggests that the online training had an overall positive impact on student scores and had helped them improve the targeted algebra skills.

3.2. Learner profiles

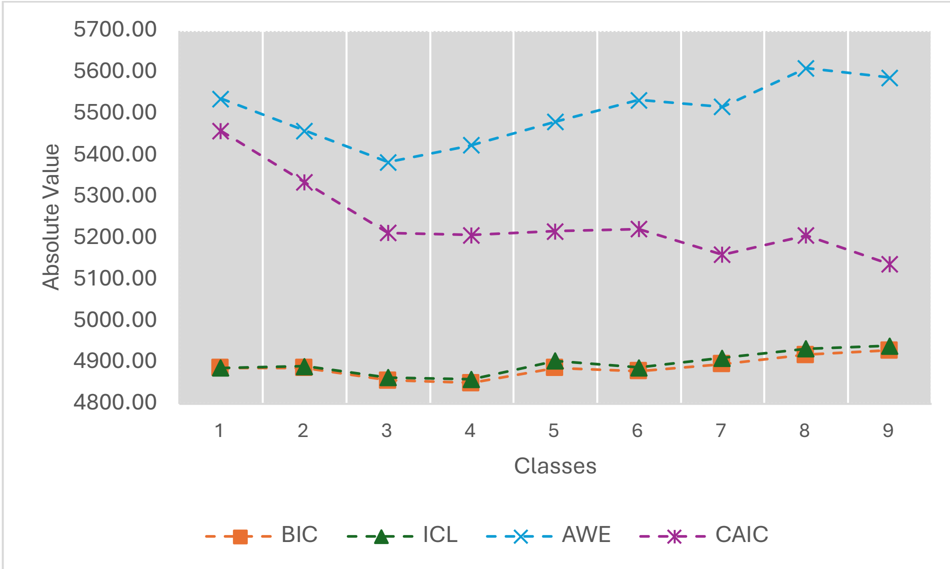
Table 1 displays the five measures employed for assessing model fit. Since BIC and ICL values that are closer to 0 indicate a better fit (Wardenaar, 2021), the values of BIC and ICL support the 4-cluster solution as the best fit. The value of AWE is lowest for the 3-cluster solution and second lowest for the 4-cluster solution. The value of CAIC is relatively low for the 4-cluster solution and lowest for the 8-cluster solution. The p value of BLRT remained non-significant until the 7-cluster solution (See Figure 2). A closer examination of the composition solutions with 6 or 8 clusters revealed, however, that the groups became less distinguishable, and some groups had only two to three members. According to Ferguson and the colleagues (2020), the final model should be interpretable and meaningful: "While it may be possible to produce models with more profiles that produce better fit, if this results in reduced distinction between profiles, … then the model with more profiles is not beneficial to theory, science, or practical application" (p.460). As a result, the 4-cluster solution was selected based on an overall evaluation of the model selection indices, the group compositions, and the interpretability of the groups.

Table 1. Latent profile analysis model fit summary with model selection indices

Model	BIC	ICL	AWE	CAIC	BLRT_p
1	-4887.15	-4887.15	5536.25	5458.51	0.01
2	-4886.58	-4890.74	5459.18	5334.83	0.01
3	-4856.96	-4863.98	5383.49	5212.60	0.01
4	-4850.92	-4859.47	5424.49	5207.08	0.01
5	-4887.20	-4903.85	5480.81	5216.82	0.01
6	-4879.35	-4888.02	5532.90	5222.40	0.01
7	-4895.82	-4910.70	5516.91	5160.01	0.97
8	-4918.58	-4933.45	5610.19	5206.76	0.01
9	-4929.39	-4940.41	5587.02	5137.12	0.01

Note. BIC: Bayesian Information Criterion; ICL: Integrated Completed Likelihood; AWE: Approximate Weight of Evidence; CAIC: Consistent Akaike Information Criterion; BLRT_p: Bootstrap Likelihood Ratio Test p-value

Figure 2. Elbow-plot of the absolute values of selected fit indices for the LPA



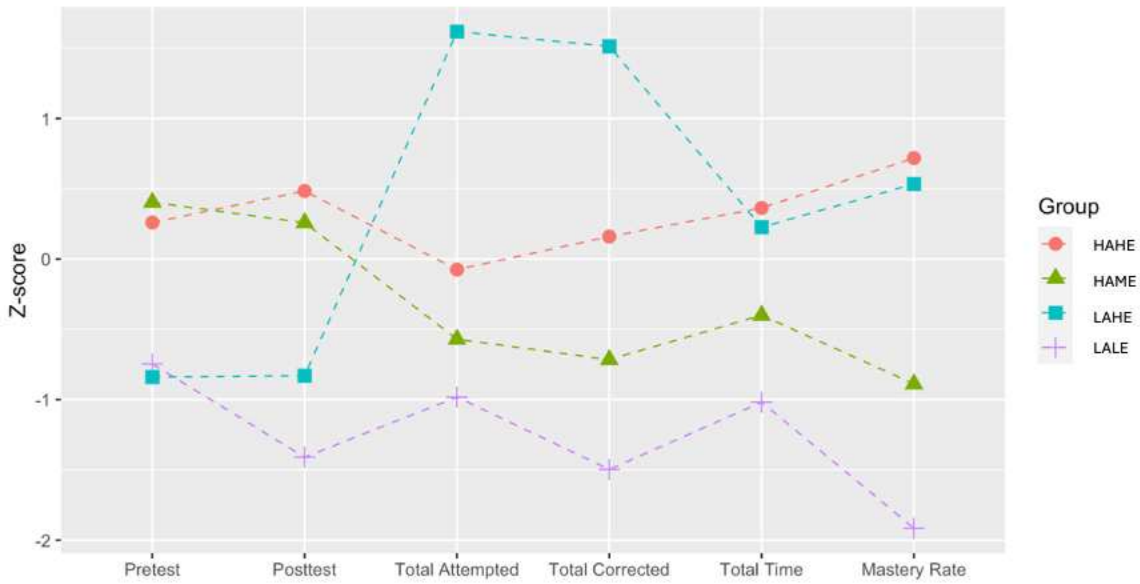
The means and standard deviations of the six measures used in the LPA are presented in Table 2. In addition, the z scores for the six measures were calculated and illustrated in Figure 3. High achiever-high engagement (HAHE) group consists of students who had relatively high pre-test scores and put a good amount of effort in the online training. They had the highest total time spent on task and the highest post-test scores. High achiever-medium engagement (HAME) group is composed of students who had similar pre-test scores as the HAHE group but worked on and mastered much less problems, thus spending much less time on task. Students in the low achiever-high engagement (LAHE) group are those who were not as strong initially but put a significant amount of effort into the online training. This is evidenced in the highest total number of attempted questions and a relatively large amount of total time they spent on the training. Finally, students in the low achiever-low engagement (LALE) group started with relatively low pre-test scores too and were the lowest in their total questions attempted, time-on-task, and mastery rate. This group of students experienced no improvement from pre-test to post-test.

Table 2. Mean (SD) of the six student performance and behavior measures by groups (n=104)

	HAHE (N=48)	HAME (n=28)	LAHE (N=17)	LALE (N=11)
Pre-test Score	9.02 (2.45)	9.27 (2.52)	5.87 (2.41)	6.17 (2.07)
Post-test Score	12.40 (2.84)	11.47 (2.85)	7.97 (2.25)	6.09 (2.05)
Total Correct	83.25 (16.81)	52.27 (14.27)	134.97 (23.28)	21.35 (14.28)
Total Attempted	134.64 (53.35)	93.46 (41.97)	289.45 (74.32)	51.43 (36.06)
Mastery Rate (prop.)	.92 (.096)	.43 (.114)	.88 (.129)	.11 (.121)
Total Time (s)	7362.47 (3905.93)	4689.17 (3313.47)	6880.29 (2763.16)	2131.04 (1779.26)

Note. HAHE = High achiever-high engagement group; HAME = High achiever-medium engagement group; LAHE = Low achiever-high engagement group; LALE = Low achiever-low engagement group.

Figure 3. Comparison of four groups' six performance and behavior measures in z-scores



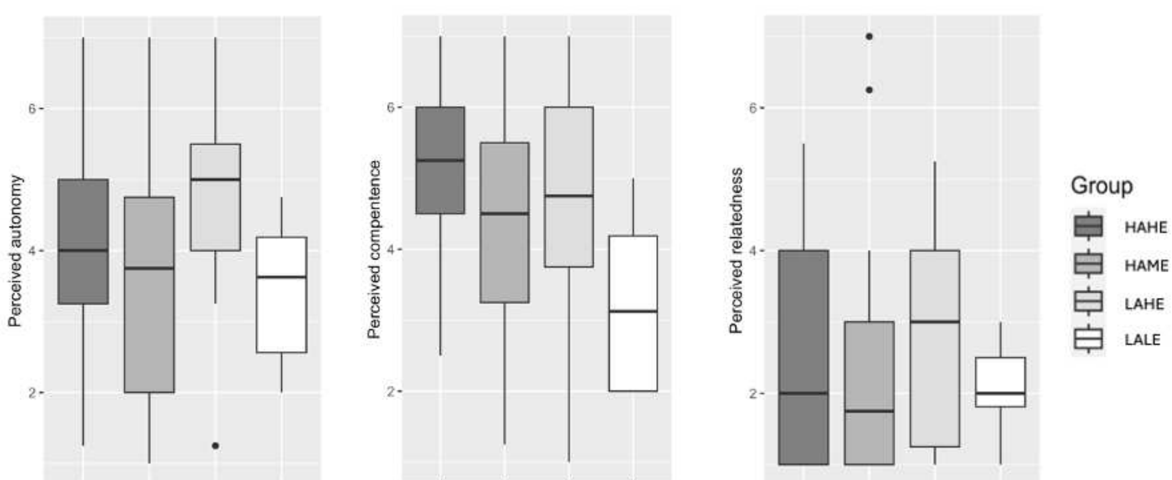
3.3. Perceived needs satisfaction in online groups

Seven students who did not participate in the survey were excluded from the analysis, leaving a total of 97 data points. Table 3 present the means and standard deviations of students' scores on perceived autonomy, competence, and relatedness satisfaction for each of the four groups, and Figure 4 shows the box plots of student perceived needs satisfaction for each group.

Table 3. Mean (SD) of autonomy, competence, and relatedness satisfaction by groups (n=97)

	HAHE (N=45)	HAME (n=25)	LAHE (N=17)	LALE (N=10)
Autonomy	4.18 (1.51)	3.51 (1.65)	4.74 (1.43)	3.48 (0.99)
Competence	5.23 (1.28)	4.33 (1.47)	4.69 (1.52)	3.20 (1.25)
Relatedness	2.37 (1.44)	2.27 (1.63)	2.79 (1.43)	2.15 (0.62)

Figure 4. Comparison of four groups of students perceived needs satisfaction



The results from the one-way MANOVA suggested that there was a statistically significant difference in student perceived needs satisfaction across the four groups ($F(9, 221) = 3.64$, $p < .001$; Wilk's $\Lambda = 0.72$, partial $\eta^2 = .11$). The follow-up ANOVAs suggested that both student perceived autonomy scores ($F(3, 93) = 2.88$; $p < .05$; partial $\eta^2 = .09$) and student perceived competence scores ($F(3, 93) = 6.89$; $p < .001$; partial $\eta^2 = .18$) were significantly different across the groups, but student perceived relatedness scores were not ($F (3, 93) = 0.60$; $p > .05$). As presented in Table 4, pairwise comparisons using Tukey's HSD post-hoc tests showed that the differences in student perceived autonomy scores almost reach the significant level of $p = .05$ ($p = .052$) between the HAME group and the LAHE group, with students in the LAHE group having a higher sense of perceived autonomy. When it comes to students perceived competence, the LAHE group exhibited significantly higher scores compared to the LALE group ($p < .05$), and the HAHE group demonstrated significantly higher scores not only when compared to the HAME group but also when compared to the LALE group ($p < .05$).

Table 4. Pairwise comparisons of perceived autonomy and competence scores

						95% Confidence Interval	
	group (I)	group (J)	Mean Difference (I-J)	SD	Sig.	Lower Bound	Upper Bound
Perceived Autonomy	HAHE	HAME	.673	.373	.278	-.303	1.650
		LAHE	-.552	.426	.568	-.167	.563
		LALE	.708	.523	.531	-.661	2.077
	HAME	LAHE	-1.225	.471	.052	-2.456	.006
		LALE	.035	.560	1.000	-1.430	1.500
	LAHE	LALE	1.260	.597	.157	-.300	2.821
Perceived Competence	HAHE	HAME	.903	.341	.046*	.010	1.796
		LAHE	.542	.389	.508	-.477	1.561
		LALE	2.033	.478	.000**	.782	3.285
	HAME	LAHE	-.361	.430	.835	-1.487	.764
		LALE	1.130	.512	.129	-.210	2.470
	LAHE	LALE	1.491	.545	.037*	.064	2.918

Note. * $p < .05$, ** $p < .001$

3.4. Perceived needs satisfaction and group composition

A multinomial logistic regression was conducted to examine whether student perceived needs satisfaction could predict the composition of the groups. The results suggested that the inclusion of the three predictors, namely perceived autonomy, competence, and relatedness, led to a significant improvement in model fit ($\chi^2 = 31.67$, $p < .001$). In Table 5, the logistic coefficient (B) shows the expected amount of change in the logit for each one-unit change in the predictor. A logistic coefficient closer to zero suggests that the predictor has less influence in predicting the logit. Notably, the analysis indicated that perceived autonomy exerted a significant effect on the odds of a student being assigned to the LAHE group in comparison to the HAHE group. Additionally, perceived competence played a significant role in predicting the odds of a student being assigned to either the LAHE group or the LALE group in comparison to the HAHE group. It's worth noting that perceived relatedness was subsequently removed from the model because the three-predictor model did not demonstrate a significant improvement over the two-predictor model, which solely included perceived autonomy and perceived competence as predictors. This two-predictor model performed significantly better than the original model ($\chi^2 = 31.26$, $p < .001$). This selection of predictors allowed for a more parsimonious yet effective model in understanding the relationships between perceived needs satisfaction and group composition.

Table 5. Results from multinomial logistic regression analysis

Predictors	HAHE vs.	B	Odds Ratio	p-value
Perceived Autonomy	HAME	-0.12	0.89	0.686
	LAHE	0.87	2.40	0.012*
	LALE	0.72	2.05	0.103
Perceived Competence	HAME	-0.47	0.63	0.082
	LAHE	-0.96	0.38	0.004**
	LALE	-1.59	0.20	0.000**
Perceived Relatedness	HAME	0.16	1.18	0.493
	LAHE	-0.01	0.99	0.967
	LALE	0.06	1.06	0.882

Note. * $p < .05$, ** $p < .005$

4. Discussion

This study investigated the online learning profiles and perceived needs satisfaction of undergraduate students who participated in an online training program aimed at enhancing their proficiency in basic algebra skills. While there was an overall improvement in student performance in these algebraic skills, not all students behaved similarly, nor did they all benefit from the online training at the same level.

The latent profile analysis unveiled four distinct groups: HAHE, HAME, LAHE, and LALE. Within the two high-achiever groups, there were notable differences in students' behaviors during the training program. The HAHE group, constituting 46.15% of the total students, spent the longest time in the system (averaging 7362.47 seconds), had a 92% mastery rate, and achieved a high level of proficiency in the post-test. Conversely, the HAME group invested significantly less time (averaging 4689.17 seconds) and mastered less than half of the practiced skills, with a 43% mastery rate. Similarly, the two low-achiever groups exhibited distinctive characteristics. The LAHE group attempted an average of 289.45 questions, achieving an 88% mastery rate. On the other hand, the LALE group completed only an average of 51.43 questions and mastered a mere 11% of the practiced skills. These findings suggest that, despite both groups starting with relatively low pre-test scores, the LAHE group displayed greater persistence and motivation in their pursuit of mastery during practice, while the LALE group appeared to disengage more quickly. Similar but slightly different patterns were reported by Mojarad et al. (2018), who identified five learner profiles for students who use an online adaptive assessment and learning system – ALEKS. These profiles are: *strugglers* with low prior knowledge and low engagement; average *students* with average prior knowledge and average engagement; *sprinter* with average prior knowledge and low engagement; *gritty* with average prior knowledge and high engagement; and *coasters* with high prior knowledge and low engagement.

The interviews yielded valuable insights that helped in understanding the behaviors and performance of these students. Among the eleven students who volunteered to participate in the interviews, eight were from the HAHE group, two from the HAME group, and one from the LAHE group. There were no participants from the LALE group.

Students within the HAHE group generally perceived the online training positively and found the questions included in the training program to be appropriately challenging. The two students from the HAME group shared their reasons for dedicating limited time to the training program. One student mentioned that he practiced less in later weeks because he encountered similar problems in subsequent assignments, making additional practice seemingly redundant. The other student explained that as the course content became more challenging, she made the decision to allocate her time to aspects of the coursework that she deemed more important, prioritizing them over the online training. The one student from the LAHE group found the existing hints in the system insufficient, especially when he repeatedly answered questions incorrectly, and expressed a desire for the online system to provide additional hints. Nevertheless, he believed that the practice contributed positively to his learning in the course. He planned to go to graduate school and needed to improve his GPA, and he attributed his grade of B in the course to the beneficial effects of the online training. Regrettably, the LALE group were not represented in the interviews.

The results revealed the differences in student perceived autonomy and competence scores across the four groups. Particularly intriguing was the significantly higher perceived competence scores of the LAHE group compared to the LALE group, despite both groups initially having relatively low pre-test scores. Similarly, the HAHE group exhibited significantly higher perceived competence scores than the HAME group, even though their pre-test scores were similar. Moreover, the LAHE group displayed higher perceived autonomy scores compared to the HAME group, with this difference approaching statistical significance. These findings suggest that individuals may perceive varying levels of competence, even if their actual performance levels are similar, and they may also perceive different levels of autonomy, even when receiving the same amount of contextual support within an online learning environment. In addition, as what previous studies have shown, perceived needs satisfaction influenced student motivation and engagement (e.g., Chiu, 2023; Mendoza et al., 2023), which may help explain the varied levels of engagement among different groups of students.

Finally, the results indicated that student perceived autonomy and perceived competence scores significantly predicted their membership in the groups. Conversely, perceived relatedness scores did not emerge as a predictor. This outcome is understandable, considering that perceived relatedness scores were consistently low across all four groups. This is likely because students in this online training environment had limited opportunities to collaborate or establish connections with their peers. They predominantly worked independently on assignments and received feedback solely on their individual performance. Since the literature has highlighted the positive role of perceived relatedness in students' engagement in online learning (Chiu, 2022), it is important to recognize that this finding should not be extrapolated to suggest that perceived relatedness would not be a significant predictor in more collaborative and connected online learning environments.

The theoretical significance of this study is multifaceted, as it not only enhances our understanding of student autonomy and competence in online learning environments but also provides valuable insights for future investigations and research into the development of tailored online learning experiences. Several key theoretical implications emerge from the findings are the following: First, one of the central theoretical implications of this study is the recognition that individuals may require different types or levels of instructional and contextual support to attain the desired levels of perceived autonomy and perceived competence. This insight calls for future research to delve deeper into the nuanced needs of students and to determine who specifically requires additional support and what forms of support are most effective for those with low levels of perceived autonomy or competence. Researchers could further explore the potential impact of individual characteristics, such as learning styles and personality traits, on their perceived autonomy or competence. This exploration could lead to the development of tailored support strategies or adaptive online learning environments that cater to the unique profiles of learners. Second, according to literature, perceived autonomy and competence has always been positively linked to persistence, effort, and goal attainment (Leondari & Gialamas, 2002; Pelletier et al., 2001; Sheldon & Elliot, 1998). The findings from this study are consistent with the literature by showing groups with relatively high perceived autonomy and competence put in greater effort in the practice. This study lays the groundwork for future research to examine the effects of interventions aimed at enhancing students' perceived competence and autonomy. Researchers can design interventions targeting autonomy and competence enhancement and assess their impact on student motivation and persistence, shedding light on the causal mechanisms at play.

Third, the study highlights the importance of understanding the underlying reasons for some students' relatively low levels of perceived autonomy and competence. It draws attention to the attribution theory, suggesting that students may attribute their failures to various factors, such as their perceived lack of abilities (Graham, 2020; Weiner, 2010). This attribution can have profound effects on students' emotions and motivation, potentially leading to shame and decreased effort (Aghaei et al., 2023). Future research can further investigate the links between attribution, motivation, and perceived autonomy and competence. It can explore approaches, such as the use of learning analytics dashboards (Aghaei et al., 2023) or gamification elements, to shift students' attributions and encourage greater effort and persistence.

The findings of this study also have significant practical implications for educators, instructional designers, and institutions engaged in online education. One of the primary practical implications is the need for instructors to identify students' perceived needs satisfaction at an early stage. By doing so, educators can tailor their instructional methods and support strategies to address the unique needs of each student. For instance, instructors can offer additional guidance, resources, or mentorship to students who have a relatively low perceived autonomy or competence. Second, to effectively support students with varying levels of perceived autonomy or competence, instructors may need to implement customized interventions. For example, instructors can design adaptive learning pathways that offer different levels of choice and support tailored to different learner profiles. Additionally, they can encourage self-assessment and reflection to help students become more aware of their own learning needs and progress. Third, instructional designers play a pivotal role in shaping online learning environments. The study highlights the importance of developing online learning environments that are adaptive to students' autonomy and competence needs. Designers can implement features that allow for flexible pacing, personalized feedback, and scaffolding of learning activities. Additionally, they can incorporate tools that empower students to take more ownership of their learning while providing adequate support for those who require it.

5. Limitations and Future Research

While this study has yielded valuable insights into students' online learning profiles and its relationship with perceived needs satisfaction, it is important to acknowledge several limitations that may impact the interpretation of the findings and suggest avenues for future research.

First, one limitation of this study pertains to the measurement of participants' time spent in the system. It is important to acknowledge that the total time spent in the system does not necessarily align with the total time spent on the learning tasks. Participants may have engaged in other unrelated activities within the system during their recorded time, potentially introducing variability and inaccuracies into our analysis. To address this issue, our study incorporated the total number of questions attempted as an additional measure to gain a more accurate understanding of the effort invested by students. Nevertheless, future research endeavors should explore alternative tracking methods to further enhance the precision of time allocation assessment within the system. Second, the sample size used in this study, while sufficient for preliminary analysis, may not fully represent the diversity and complexity of the target population. A larger and more diverse sample would confirm the stability and applicability of the identified profiles and enhance the generalizability of the findings. Third, interviews were employed as the complementary data collection method in this study to understand the underlying causes of different profiles. It is important to recognize that, in this study, interviews were not able to reach those who are less inclined to participate, specifically, students in the LALE group. Future research should explore alternative data collection methods to reach all groups under investigation.

6. Conclusion

In conclusion, this study holds significance in online learning research for several reasons. First, it goes beyond the conventional assessment of the overall effectiveness of online learning environments and delves deeper into the intricate dynamics of online learning, shedding light on how diverse groups of students responded differently to the same intervention. By doing so, it highlights the importance of investigating individual differences in online learning research. Furthermore, the identification of distinct groups and the exploration of the factors contributing to their varying performances pave the way for a more nuanced and tailored approach to online learning. By gaining insights into the unique challenges and strengths of each group, researchers and educators are better equipped to design adaptive online learning environments, ultimately benefiting students in diverse online learning contexts. Finally, the study offers practical implications by suggesting the importance of identifying students' skill levels and perceived needs satisfaction early in their online learning. This proactive approach can enable instructors to provide timely and targeted support, aligning educational interventions with the diverse needs and preferences of students.

7. References

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