

Article

Sustainable Technology Integration in Underserved Area Schools: The Impact of Perceived Student Change on Teacher Continuance Intention

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Received: 22 May 2020; Accepted: 9 June 2020; Published: 12 June 2020



Abstract: This study aims to examine the determining factors of teachers' continuance intention to integrate technology in a smart classroom of schools in underserved areas. Smart classrooms provide a supportive learning environment for students by equipping them with advanced multi-functional and mobile technologies. A smart classroom can provide opportunities for teaching and learning by facilitating curriculum implementation and encouraging student success. The sustainable integration of technology in a smart classroom depends on the teacher's ability to effectively utilize digital technology in the classroom. We assessed teachers' perceptions of their technology integration by building a research model for sustainable technology integration in an underserved area in South Korea. For this, we included four aspects of teachers' perceptions: the frequency of technology integration, the effort toward instructional practices, student change, and continuance intention. Data were gathered via a self-administered online survey with a sample of teachers who are participating in a smart school program and were analyzed using partial least squares structural equation modeling. The findings of the study show that teachers in smart classrooms are motivated to continue technology integration when they experience positive changes among students after employing smart classroom technologies. The research findings can contribute to the efforts of educators, scholars, and policy-makers to pursue sustainable development in underserved area schools.

Keywords: digital classroom; technology integration; rural education; teacher perceptions; smart classroom

1. Introduction

With the increased availability of smart technologies and high-speed Internet, educational informatization has become an important aspect of enriching students' experiences as well as improving educational administration and management [1]. Emerging technologies are becoming an increasingly vital part of education, both in terms of providing instructional tools and in shaping curricula. Most school curricula have adopted information and communication technologies as an integral part of teaching and learning. The availability of digital technology has been perceived as a social equalizer and a means of sustainable development in education [2]. Yet, rural areas with students from low-income families, who have low motivation and lower academic performance, are still at a digital disadvantage thanks to various constraints such as the availability of financial and human resources and the limits of geographical isolation [3,4]. Digital technologies offer opportunities for excluded learners and learners at risk of exclusion by providing resources for teachers and students in underserved area schools [5]. However, with unequal access to high-quality educational resources, the gap between urban and rural education remains [2].

In harnessing digital technologies for sustainable development in underserved area schools, the key to successful implementation is teachers who have the pedagogical capability to integrate technology into existing curricula [6–8]. The role of the teacher in a technology-integrated classroom is to effectively utilize digital technology to promote student engagement and reach target learning outcomes [9]. However, rural schools face ongoing practical disadvantages. For example, teachers are often responsible for multiple subjects and grades in a single classroom while also holding additional responsibilities such as leading extracurricular activities and providing support programs and infrastructure for students' success [10]. The challenges teachers face can hinder the innovation that might bridge the gap in student performance caused by the geographical location of the school and/or the social background of the students [11]. Major factors for the sustainable integration of technology in the classroom include professional development in technology integration; the accessibility of technology equipment; the development of technology-integrated curricula; school climate and culture; and teacher motivation, which can be influenced by self-efficacy, internal and external values, and the intention to use [6,12].

2. Background and Hypotheses

The traditional teacher-centered approach to learning can be amended by digital technology, which provides the tools to transform classrooms into student-centered environments and enhance the engagement of both teachers and students [13–15]. Smart classrooms integrate advanced technologies to increase teachers' instructional capabilities and engage students in their learning experience [13,15–18]. The multi-functionalities and connectivity of advanced technologies as well as pedagogical capabilities in smart classrooms enable a more student-centered environment by facilitating a 1:1 setting. Smart classrooms provide an alternative solution to educational opportunities not typically available in underserved area schools. The adoption of advanced technologies in smart classrooms requires teachers to integrate technology into their pedagogical activities and to continue doing so in the long term [12].

2.1. Technology Integration in Smart Classrooms

Smart classrooms can broaden teachers' pedagogical imaginations and students' active engagement without alienating them during instruction. Smart classrooms are equipped with modern technologies such as tablets, interactive whiteboards, high-speed networks, learning management systems, applications, and other educational resources to support the teacher and students [19–21]. The emergence of mobile handheld devices in the classroom can foster a more interactive environment that encourages students to actively engage in the learning process and contribute to their learning experience [14,22]. Interactive and cooperative digital learning technologies enable engagement, such as cloud-based learning management systems, touch-screen electronic whiteboards with shared classroom materials, authoring tools for digital textbooks, and learning resources for mobile handheld devices [23]. When smart classrooms were conceptualized [24,25], they were focused on the use of technology in traditional teaching contexts. Then, evolving mobile technologies facilitated hyper-personalized learning [19], more advanced interactivity between teacher and students and among students, and access to a wide variety of instructional content and applications.

One of the goals of smart classrooms is to address student disengagement from learning. The classroom ratio of one teacher to many students has been the norm for a long time. Student disengagement in public schools has been a serious detriment to their academic achievement and satisfaction [26], and can often be attributed to factors such as a high student-to-teacher ratio, limited classroom space, socioeconomic status, and other socio-cultural factors [27–29]. Students in public schools in underserved areas are more likely to be disengaged in the classroom due to the lack of available resources, geographical isolation, and limited support [26]. Smart classroom technology can resolve disengagement when the goals of technology use and teachers' preparedness are aligned, and when students demonstrate positive changes in the new, technology-driven environment [30,31]. The primary reason students do not succeed in school is lack of appropriate methodology and materials to motivate student interest, thus indicating the need for

technology [31]. Technology can assist teachers in capturing learners' attention in a variety of ways that traditional methods cannot [31]. Due to the availability of many types of technology, learners with different needs and learning styles can be engaged and motivated toward learning [30,31]. For example, instructional presentation has been improved through the use of interactive whiteboards, PowerPoint, and VoiceThread, which support visual and auditory learners [30,31]. The use of tablets can further improve learning based on students' interest; several educational apps are available and students can choose what appeals to them [32].

2.2. Teachers' Technology Integration and Perceived Student Change

When teachers implement new instructional practices, a negative response from students can discourage teachers from continuing to use the new method or explore other practices [33]. According to Howley, Wood, and Hough [6], teachers in rural schools are influenced by students' attitudes, preparedness for using technology, and the availability of technology, rather than the school's location or students' socioeconomic status. Technology can play a significant role in students' lives and education, and teachers have a profound influence on the way technology is integrated into lessons. The integration of technology in smart classrooms is possible only when teachers take the time to become familiar with the technology and acquire the equipment needed to support learning. Beyond this, teachers must find ways to incorporate the new technology into their teaching. This must be done in such a way that the teaching provides complex cognitive engagement that, in turn, invites students to become invested in the learning process [34]. Teachers' appropriate integration of technology in smart classrooms may have a positive influence on student change. We therefore hypothesize the following relationship:

Hypothesis 1 (H1). *The frequency of technology-integrated instruction in smart classrooms has a positive influence on teacher-perceived student change.*

2.3. Teachers' Technology Integration and Effort toward Instructional Practices

The effectiveness of technology integration in schools is dependent on teachers' actual practice, the ability to integrate technology, their training in technology, the availability of educational software, and the degree to which school infrastructure supports integration [35,36]. In smart classrooms, teachers need to implement new technologies based on a student-centered approach to teaching that fosters technology-appropriate skills, knowledge, and attitudes. The technologies in smart classrooms support student-centered learning in more constructivist ways [15]. Recently, the shift from teacher-centered to student-centered learning in the educational paradigm has altered teachers' beliefs about successful instruction. It is important to be consistent in the use of technology even if teachers apply it in simple ways [37]. Teachers' effort toward instructional practices, including professional development and the application of innovative instructional methods, can manifest in several ways at the personal, school, district, and national levels. These efforts can impact instructional effectiveness, knowledge, skills, and student growth as perceived by teachers. However, teachers' ability to practice in innovative environments such as smart classrooms has been hampered by the absence of professional development and related equipment. Thus, teachers in favor of technology integration should ensure the localization of their professional experiences to increase the effectiveness of instructional practices in the classroom [38,39]. Teachers' efforts to adopt technology-based instructional practices into the classroom can catalyze technology-integrated classrooms, whereas teachers who make little effort have little influence on classroom changes. Thus, we hypothesize the following relationships:

Hypothesis 2 (H2). *The frequency of technology-integrated instruction in smart classrooms has a positive influence on teachers' effort toward instructional practices.*

Hypothesis 3 (H3). *Teachers' effort toward instructional practices in smart classrooms has a positive influence on teacher-perceived student change.*

2.4. Perceived Student Change and Teacher Continuance Intention

According to technology acceptance models regarding technology integration [40–42], teachers' continuance intention toward technology use is connected to their actual use of technology in classrooms [9]. Thus, teachers' continuance intention toward technology integration in smart classrooms is an important predictor of long-term practice. However, teachers in rural schools have difficulties sustaining technology integration due to insufficient time, technical limitations, and inadequate support [43]. These difficulties may partly be the result of a passive approach toward technology integration—an unsupportive environment can provoke negative attitudes toward the technology-integrated environment. Teachers' perception of student characteristics and behaviors can also influence teachers' implementation and continuance of new and innovative practices [33]. To examine the relationship between student change and teacher continuance intention toward technology integration in smart classrooms, we postulate the following:

Hypothesis 4 (H4). *The frequency of technology-integrated instruction in smart classrooms has a positive influence on teachers' continuance intention toward technology integration in the classroom.*

Hypothesis 5 (H5). *Teachers' efforts toward instructional practices in smart classrooms have a positive influence on teachers' continuance intention toward technology integration in the classroom.*

Hypothesis 6 (H6). *Teacher-perceived student change has a positive influence on teachers' continuance intention toward technology integration in the classroom.*

The research model for this study is shown in Figure 1.

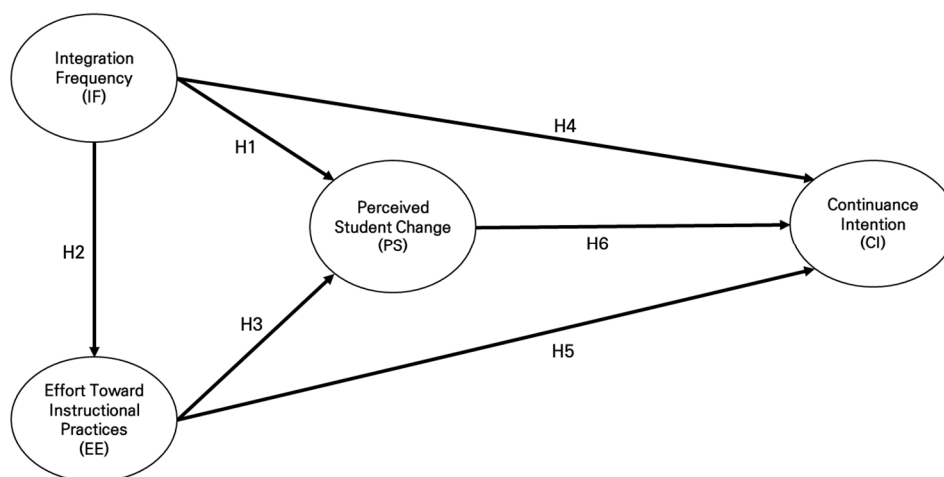


Figure 1. The research model.

3. Materials and Methods

3.1. Sample and Data Collection

A total of 54 respondents from 21 elementary and middle schools participated in this study, including teachers who work in smart classrooms donated by a community relations program for underserved rural schools and education institutions (e.g., hospital schools and community youth centers). The classrooms have been provided with high-tech learning environments and mentoring

groups since 2012. The program donates to around ten educational institutions each year. Teachers who were working in such classrooms at the time of this study were invited to participate in a survey to assess their experience in the smart classrooms. Therefore, the number of possible respondents was limited. Basic background information regarding the participants is shown in Table 1.

Table 1. Descriptive statistics.

Background Information		Frequency	%
Gender	Female	24	42.6
	Male	30	57.4
School Level	Elementary school	37	68.5
	Middle school	17	31.5
Age	20–25	3	5.5
	26–30	11	20.4
	31–35	15	27.8
	36–40	12	22.2
	41–45	7	13.0
	46 (or older)	6	11.1
Teaching Experience	5 years or less	23	42.6
	6–10 years	10	18.5
	11–15 years	11	20.3
	16–20 years	4	7.4
	21–25 years	3	5.6
	26 years or more	3	5.6

An online survey was conducted via SurveyMonkey, an online survey tool, to collect data regarding teachers' experiences operating in smart classrooms.

3.2. Measures

All variables were measured according to criteria developed by the researchers. The background information for the teachers included gender, the school level they were teaching, age, years of teaching experience, and their technology proficiency level. Additionally, the frequency of technology integration was measured by three items using a 7-point scale (Cronbach's alpha = 0.77); for example, "How many times have you used the smart classroom environment for your instruction in the last month?" Teacher-perceived student change in smart classrooms was measured by four items [44,45] using a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree (Cronbach's alpha = 0.92); for example, "During my instruction in the smart classroom, students were actively engaged." Continuance intention was measured by two items [42,46,47] using a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree (Cronbach's alpha = 0.79); for example, "I have continuously used the smart classroom environment because of students' satisfaction with it in previous classes." Teachers' effort toward instructional practices (EE) was measured by two items [15,48,49] using a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree (Cronbach's alpha = 0.91); for example, "I made an effort to improve my instructional skills for the smart classroom."

3.3. Data Analysis

Data were analyzed using partial least squares structural equation modeling (PLS-SEM) to evaluate the quality of the model and test the hypotheses. We used PLS-SEM because it can handle non-normal data, as well as smaller sample sizes [50]—our sample size of 54 teachers was relatively small. To validate the model, we used convergent validity and discriminant validity [50]. To examine loadings, weights, average variance extracted (AVE), composite reliabilities (CR), and t-values, we performed the bootstrapping process with 5000 resamples. Fornell and Larcker propose a cutoff value of 0.70 or greater as being acceptable for CR [51]. Both validities can offer proof of the goodness of fit of the

model regarding the collected data [40]. The statistical analysis in this study was conducted using SPSS 26.0 for descriptive statistics of the data and using SmartPLS [52]. This study followed the guidelines of PLS-SEM provided by Hair and colleagues [50,53].

4. Results

4.1. Evaluation of the Measurement Model

The properties of the measurement model were examined using convergent validity and discriminant validity. Convergent validity can explain the indicators' variance, which is the shared variance between each item and its associated construct. The standardized loadings for each factor model should exceed 0.70 [50]. As shown in Table 2, the standardized loadings of all items exceeded this threshold. Additionally, the AVE, which measures the variance captured by the indicators relative to the variance caused by the measurement errors of the indicators, should exceed 0.50 [51]. The acceptance level of AVE was 0.5 or higher, which means that 50% or more of the indicators' variance is accounted for by the construct. Table 2 shows that all constructs met this threshold.

Table 2. Item reliability and convergent validity analysis.

Latent Variable	Indicator	Loading	Alpha	CR	AVE
Continuance Intention (CI)	CI1	0.935	0.791	0.904	0.825
	CI2	0.881			
Perceived Student Change (PS)	PS1	0.913	0.916	0.941	0.799
	PS2	0.933			
	PS3	0.874			
	PS4	0.854			
Integration Frequency (IF)	IF1	0.732	0.766	0.866	0.685
	IF2	0.831			
	IF3	0.910			
Effort toward Instructional Practices (EE)	EE1	0.951	0.911	0.957	0.918
	EE2	0.964			

Note: CR = Composite Reliability; AVE = Average Variance Extracted; Alpha = Cronbach's Alpha.

To confirm the construct reliability, the values of Cronbach's alpha and composite reliability should exceed the threshold of 0.70 [54]. As shown in Table 2, the alpha from each response showed a range of 0.766 or higher, yielding an internal consistency that exceeded the necessary threshold. The CR values were in the range of 0.866 to 0.957, which exceeded the threshold of 0.80, showing that the reliability of respondent scores was adequate with relatively little errors [54]. Thus, the results of the standardized loadings, Cronbach's alpha, CR, and AVE support the convergent validity and reliability of the measurement model.

The discriminant validity was assessed using the Fornell–Larcker scale and cross-loadings, as shown in Table 3. To confirm discriminant validity, the square root of AVE should be higher than all correlations between constructs [55], which are given by the bold diagonal elements in Table 3. The off-diagonal values represent the correlations between the constructs. As can be seen in Table 3, the square root of each construct's AVE was higher than the correlations between the constructs. The square root of the AVE for a construct should be significantly higher than the variance between that construct and other constructs within the model [50]. The square root of the AVE should also be greater than 0.5 [55]. Table 4 shows the analysis of the correlations among the measurement items to confirm that they do not cross-load on other factors. All items loaded higher than their own construct and had a value higher than 0.5. Thus, all values were higher than the requisite thresholds and the discriminant validity in the measurement model was confirmed.

Table 3. AVE and the correlations of all constructs for discriminant validity.

Latent Dimensions	CI	PS	IF	EE
Continuance Intention (CI)	0.908			
Perceived Student Change (PS)	0.685	0.894		
Integration Frequency (IF)	0.446	0.515	0.828	
Effort toward Instructional Practice (EE)	0.381	0.454	0.330	0.958

Note: The bold diagonal elements represent the square root of AVE; the off-diagonal elements represent correlations between the constructs.

Table 4. Cross-loading of discriminant validity analysis.

Latent Variable	Indicator	CI	PS	IF	EE
Continuance Intention (CI)	CI1	0.935	0.699	0.469	0.390
	CI2	0.881	0.524	0.324	0.291
Perceived Student Change (PS)	PS1	0.593	0.913	0.527	0.437
	PS2	0.614	0.933	0.491	0.341
	PS3	0.652	0.874	0.454	0.424
	PS4	0.588	0.854	0.361	0.422
Integration Frequency (IF)	IF1	0.302	0.394	0.732	0.237
	IF2	0.344	0.312	0.831	0.346
	IF3	0.446	0.544	0.910	0.249
Effort toward Instructional Practice (EE)	EE1	0.347	0.413	0.272	0.951
	EE2	0.381	0.454	0.354	0.964

Note: The bold diagonal elements represent the square root of AVE; the off-diagonal elements represent correlations between the constructs.

4.2. Structural Model Evaluation and Hypothesis Testing

After evaluating the measurement model, we examined the structural model proposing that there are causal relationships between constructs. The bootstrapping method was run using 5000 samples, as well as bias-corrected and accelerated (BCa) confidence intervals with a two-tailed test at a 0.05 level. The structural model was assessed according to the significance of the path coefficients, the level of predictive power of the model using R^2 value and Q^2 of the endogenous variables, and the f^2 effect size.

All path coefficients of the model were statistically significant. As shown in Table 5 and Figure 2, the results support all four hypothesized paths. The relationship between IF and EE was accepted, with an effect size that proved to be small ($\beta = 0.330$, $p = 0.017$). The relationship between EE and PS was accepted, also with a small effect size ($\beta = 0.319$, $p = 0.009$). The relationship between IF and PS was accepted, with a medium effect size ($\beta = 0.410$, $p = 0.000$). The relationship between PS and CI was accepted, with an effect size that proved to be large ($\beta = 0.685$, $p = 0.000$).

Table 5. Hypotheses, path coefficients, and results.

Hypothesis	Path	Path Coefficient	T-Statistics	p-Value	f^2	Conclusion
H1	IF \rightarrow PS	0.410	3.629	0.000	0.232	Supported
H2	IF \rightarrow EE	0.330	2.400	0.017	0.122	Supported
H3	EE \rightarrow PS	0.319	2.613	0.009	0.141	Supported
H4	IF \rightarrow CI	0.119	0.120	0.322	0.232	Not supported
H5	EE \rightarrow CI	0.074	0.524	0.600	0.008	Not supported
H6	PS \rightarrow CI	0.685	7.060	0.000	0.437	Supported

Note: IF = Integration frequency; EE = Effort toward instructional practice; PS = Perceived student change; CI = Continuance intention.

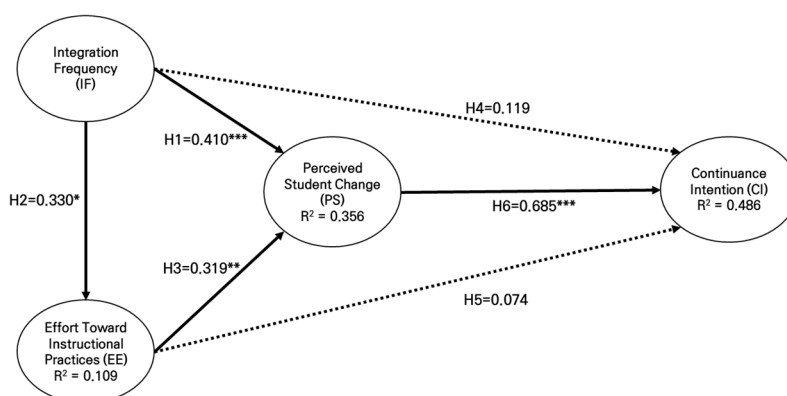


Figure 2. Results of the research model. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The coefficient of determination of the R^2 value was determined by the predictive accuracy of the model. The R^2 value can be confirmed at 0.67 or higher, with values ranging between 0.33 and 0.67 being considered moderate, values in the range of 0.19 to 0.33 as weak, and values lower than 0.19 as unacceptable. Hair et al. [50] suggested that a value of 0.25 indicates a weaker predictive relationship while a value of 0.50 indicates a medium predictive relationship. The R^2 for EE was 0.131, meaning that 13.1% of the variance in EE can be explained by this model. The R^2 for PS was 0.365, meaning that 36.5% of the variance in PS can be explained by this model. The R^2 for CI was 0.510, meaning that 51.0% of the variance in CI can be explained by this model. Additionally, the predictive relevance of the model was assessed by calculating Stone–Geisser’s Q^2 values [56,57]. The Q^2 values were 0.07 for EE, 0.334 for CI, and 0.258 for PS. All values of Q^2 reached acceptable levels of predictive relevance [58].

Further, we examined the effect size for the antecedents of endogenous variables using the value of Cohen’s f^2 [59] shown in Table 5. According to Cohen’s guidelines, f^2 is a useful measure of effect size, where $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$ represent small, moderate, and large effects of the exogenous latent variable, respectively [59,60].

As shown in Table 6, to assess the effects of specific paths in the model, we examined the mediation effect of student change (PS), teacher effort toward instructional practices (EE), and integration frequency (IF) on continuance intention (CI) using specific indirect effects after testing the bootstrapping routine with the 5000 samples, and no sign changes for determining the 95% and BCa confidence intervals in PLS-SEM [61–63]. The results of the mediation analysis showed that teacher-perceived student change is the only significant mediator between integration frequency (IF) and continuance intention (CI).

Table 6. A summary of mediation effects.

Mediation Path	Effect	T-Statistics	p -Value	95% Bias-Corrected Confidence Interval	Mediation Effect
IF → EE → CI	0.024	0.447	0.655	LLCI: −0.003, ULCI: 0.175	No
IF → PS → CI	0.242	2.592	0.010	LLCI: 0.091, ULCI: 0.451	Yes
EE → PS → CI	0.189	1.725	0.085	LLCI: 0.026, ULCI: 0.435	No
IF → EE → PS → CI	0.062	1.160	0.246	LLCI: 0.003, ULCI: 0.212	No
IF → EE → PS	0.105	1.456	0.145	LLCI: 0.008, ULCI: 0.288	No

Note: IF = Integration frequency; EE = Effort toward instructional practices; PS = Perceived student change; CI = Continuance intention; LLCI = Lower-level confidence interval; ULCI = Upper-level confidence interval.

5. Discussion

The goal of this study was to examine the role of teacher-perceived student change and teacher continuance intention in integrating technology in smart classrooms in underserved area schools. We developed six hypotheses to examine the role of key variables on teachers' continuance intention toward technology-integrated instruction in smart classrooms in rural schools.

Overall, except for hypotheses H4 and H5, our hypotheses were mostly supported by the data collected in the study. Also, we found that teacher-perceived change is the only significant mediator between the frequency of technology integration in smart classrooms and continuance intention. Hence, if those teachers who are integrating technology in underserved area schools experience positive changes in student engagement, they will be motivated to sustain technology integration in smart classrooms.

To sustain technology integration in the classroom, teachers need to be both passionate and professional [64]. In underserved schools with limited environments and educational resources, teachers have an even greater role in bringing about positive changes in the classroom. Smart classrooms as an innovative learning environment in underserved area schools should bolster teachers' continuous effort to help students actively engage in the classroom through professional development and instructional practices.

Importantly, the direct effect of frequent technology integration in smart classrooms on continuance intention is mediated by teacher-perceived student change in such classrooms, which may work as a motivational factor for teachers to sustain instruction long term. The functionalities and pedagogical possibilities of smart classrooms can enhance students' experiences in learning. Providing active and interactive technologies in a smart classroom may augment rural students' learning experiences and motivation [65]. Further, people's behavioral intention toward technology can strongly predict their actual use of technology. Smart classrooms can provide a richer learning environment for students and teachers in rural areas if teachers can consistently and effectively integrate technology into their classroom teaching. In this study, we expected to validate a research model to explain teachers' experiences in smart classrooms in order to promote more successful integration of technology in underserved area schools. The characteristics of underserved area schools were taken into consideration to develop a plan for initiating positive change among students via technology integration.

Technology integration tends to confront several challenges, including the lack of training, nonexistent equipment, and insufficient time in the curriculum to incorporate technology, among others [6], often because of the challenges of adapting an appropriate educational program to accommodate instruction goals or strategies [66]. However, recent classroom technologies with greater mobility, interconnectivity, and multi-functionality can help to overcome the limits of previous classroom technology integration using primarily personal computers. Technology integration is an authentic instructional strategy to enhance students' ability to connect what they learn to their everyday lives [67]. Through technology, teachers can not only improve their teaching efficiency, but extend and transform learning [68].

Contrary to our expectations, we found that frequent integration itself does not directly predict teachers' continuance intention toward integration in smart classrooms. The relationship can be explained by teacher motivation. Teachers' ultimate role is to support student growth through curriculum and pedagogical expertise within enriched educational environments, including resources, policies, and budget. However, in the limited environment of underserved areas, an innovative learning environment cannot be sustained by teachers alone without additional effort or motivation, such as positive changes observed in students.

This implies that technology integration in smart classrooms should be designed to ensure the enrichment of student learning, rather than rote adoption without a plan. Teachers need to experience students' positive responses, such as strong engagement in learning activities for their level of performance, gaining knowledge in subjects, or enjoying the activities in a way that reinforces their motivation to learn. When teachers perceive positive changes in students, they tend to sustain

their efforts and try new methods going forward. Positive change is a strong motivator for teachers in smart classrooms.

This study has several limitations that should be considered. First, the findings may not generalize to a more representative sample because the survey data came from underserved rural areas in South Korea, among teachers who are engaged in a specific smart school program. Second, all of the measurements of the study are limited to the teachers' self-reported perceptions. Third, the sample size is relatively small, which might limit the power of the study. Thus, increasing the sample size to provide stronger evidence for the research model will be an important undertaking for future studies. It may also prove beneficial to expand the research model to include additional predictors of teacher's technology integration in rural areas. Fourth, it is necessary to examine qualitative responses from the teachers to expand the research model as well as generalize it in different contexts.

6. Conclusions and Future Research

In conclusion, our results show that teacher perceived student change affects their continuance intention as it relates to technology in smart classrooms. The results indicate that teachers' continuous integration of technology in smart classrooms might be encouraged through motivation and additional training on using technology in their lessons. Hence, we recommend that school leaders and teacher educators support the continuous integration of technology by helping teachers use a more student-centered approach that builds toward student satisfaction and achievement. The study results will help teacher educators to plan training for in-service teachers in underserved area schools. In future studies, the research model's predictive ability and explanatory powers should be further validated regarding their usefulness in urban contexts. While our data are from underserved area schoolteachers in South Korea, additional studies may be able to generalize the findings to other areas and countries. Furthermore, comparative studies across countries could be conducted to identify the cross-country invariant variables that influence teachers' continuous intention to integrate technology in underserved area schools.

Author Contributions: H.J.K. conceived the research idea and designed the research framework; H.J.K. analyzed the data; and H.Y.J. and H.J.K. wrote the draft. All authors have read and agreed to the published version of the manuscript.

Funding: The authors acknowledge support from the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (project NRF-2017S1A5A8021541). The views expressed in this article are those of the authors and do not necessarily reflect those of the grant agencies.

Acknowledgments: The authors want to thank their anonymous reviewers.

Conflicts of Interest: The authors declare no conflict of interest.

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