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Factors Affecting Teachers' Behavior of Innovative Teaching with Technology: Structural Equation Modelling

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Abstract: This study aimed to investigate factors that predict Indonesian primary school teachers' behavior of innovative teaching with technology (BITT). A survey instrument was adapted and validated through content validity, a pilot test, and a measurement model in partial least square structural equation modeling (PLS-SEM). We obtained data from 868 primary school teachers, analyzed through a structural model in PLS-SEM and multivariate analysis of variance (MANOVA) in SPSS. The structural model was computed with several statistical reports, including the path coefficient (β), effect sizes (f^2), coefficient of determination (R^2), and predictive relevance (Q^2). MANOVA results informed t and p values. Findings indicated that four out of six hypotheses significantly predicted primary Indonesian teachers' BITT. The most substantial relationship emerged between group learning and BITT. Meanwhile, the weakest correlation was between innovative culture and BITT. Two insignificant predictors of BITT were job autonomy and innovation compatibility. Most variables showed insignificant differences based on gender. However, some variables, such as benefits of innovation, innovation compatibility, innovative culture, group cohesion, and BITT, varied significantly based on location. The study may help teachers and policymakers understand BITT elements that encourage primary school teachers to use technology creatively.

Keywords: innovative teaching; primary school; teachers; technology integration

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1. Introduction

Digital technology is essential for improving communication and collaboration in education, and this was particularly true during the COVID-19 pandemic [1]. Academics should promote the idea of developing new strategies and approaches for teachers using technology during teaching [2,3]. Furthermore, teachers should act as pioneers to produce a practical change with new teaching tools, approaches, methods, curriculums, and technologies to improve the quality of education [4]. Educational standards expect teachers to use digital technology to enhance teaching and learning activities. In preparing teachers, concerns emerged about a mismatch between teachers' skills obtained in their teaching practices and the skills required in the natural field of education. Most teachers have limitations in technological knowledge, support, creativity, and training [5]. With an increasing number of digital tools, teachers are also expected to develop and implement innovative methods to improve the quality of their students' educational experiences [6]. This transition necessitates technological proficiency and a disposition that prioritizes experimentation and creativity.

Prior studies in technology integration have revealed factors affecting teachers' technology integration, such as subjective norms, attitude, facilitating conditions, and perceived behavioral control [6–10]. However, reports on factors predicting the behavior of innovative teaching with technology (BITT) are limited when teachers develop and apply new ideas to use technology in distance teaching. Insights on technology integration in education during the COVID-19 pandemic are also crucial for future pandemics. Furthermore, path analysis, supported by demographic information differences, benefits future studies and policy development accordingly [11,12]. This research highlights best practices, obstacles, and effective methods for distant and hybrid learning environments by investigating how digital tools were used to ensure learning continuity. Specifically, the following research questions are explored in the current study:

1. How do technology innovation acceptance and organizational innovation climate influence BITT?
2. What are the differences of all latent variables based on the gender and location of the respondents?

1.1. Technology Innovation Acceptance

Technology innovation acceptance in this study is hypothesized to influence teachers' BITT during their teaching. Technology innovation acceptance consists of the benefits of innovation and innovation compatibility. The benefits of innovation refer to teachers' awareness of the positive function of technology for teaching with innovation. As teachers embrace innovation, they recognize the growing advantages of incorporating technology into their teaching methods, such as utilizing social media [13], video editing applications [14], and virtual reality [15]. Previously, Nikolopoulou and Gialamas [16] reported that teachers could gain information or learn new things comfortably when they accepted technology innovation. In addition, teachers' innovation compatibility is defined as performing innovative teaching activities that reflect merits and experiences to fulfill students' needs [17]. Recent research has linked the openness to adopt technology innovation to BITT, which is educators' desire and preparedness to use technology to improve instruction [13,14,16,17]. Teachers open to using new technology are more likely to create creative, engaging lesson plans that include digital resources, improving learning outcomes [15]. Technology-focused professional development and training can boost teachers' confidence and BITT [13]. Creating a favorable climate that supports technology innovation and offers proper support is crucial to improving teachers' behavioral intention to integrate technology into their courses. When technology innovation acceptance (i.e., the benefits of innovation and innovation compatibility) is improved, the adoption of BITT will possibly be better.

H1. *Benefits of innovation will directly and positively influence BITT.*

H2. *Innovation compatibility will directly and positively predict BITT.*

1.2. Organizational Innovation Climate

This study characterizes the organizational innovation climate as the way that teachers perceive the environments that impact technology integration, peers, schools, and leaders. Teachers' perceptions include creative and critical thinking encouragement for their students. Providing teachers with technological devices to support instructional activities also defines the organizational innovation climate [18,19]. In this study, four sub-constructs of the organizational innovation climate (group learning, group cohesion, innovative culture, and job autonomy) are hypothesized to significantly predict BITT. Davis et al. [20] have suggested that an appropriate organizational innovation climate can enhance actual behavior. When the organizational innovation climate is strong, the effort to motivate teachers for BITT will be more flexible and manageable.

Similarly, the proper ambiance of schools for group learning, group cohesion, innovative culture, and job autonomy will increase the teachers' innovation and creation of technology application during teaching to improve students' performance, motivation, capacity, and creativity [8]. Teachers are motivated to use technology when their organization has a strong innovation culture. Studies have shown that teachers feel more empowered to try novel teaching methods and technologies in schools that promote group learning, cohesiveness, and innovation [8,18,19]. Schools with a culture of cooperation and innovation are more successful at incorporating new technology because teachers feel supported and encouraged to take chances and share their experiences. A supportive environment that stresses professional autonomy allows instructors to be more creative in using technology to improve student performance. Autonomy-supportive workplaces increase intrinsic motivation, leading to more innovative teaching techniques [8]. Such venues allow teachers to try new digital tools, improving student performance, motivation, and creativity [7]. Teachers in such environments are more likely to build digital capabilities, which improves student engagement and learning. Creating a solid innovation climate in schools is crucial to improving teaching and student outcomes.

H3. *Group learning will directly and positively predict BITT.*

H4. *Group cohesion will directly and positively influence BITT.*

H5. *Innovative culture will directly and positively predict BITT.*

H6. *Job autonomy will directly and positively predict BITT.*

1.3. Demographic Information

In addition to the structural model, we added demographic data to further understand how variables vary based on gender and location. Previous studies have examined demographic disparities for technology integration in education [6,10]. Ramirez-Correa et al. [10] found that gender differences in technology integration for learning through multimedia and computer adoption were significant. Regional differences significantly varied learning behavioral patterns in both rural and urban areas. Urban area students have better performance in learning behavior than that of their counterparts [21,22]. In Indonesia, urban and suburban areas influence many educational activities [21]. Thus, this study included two hypotheses based on gender and school location (Figure 1).

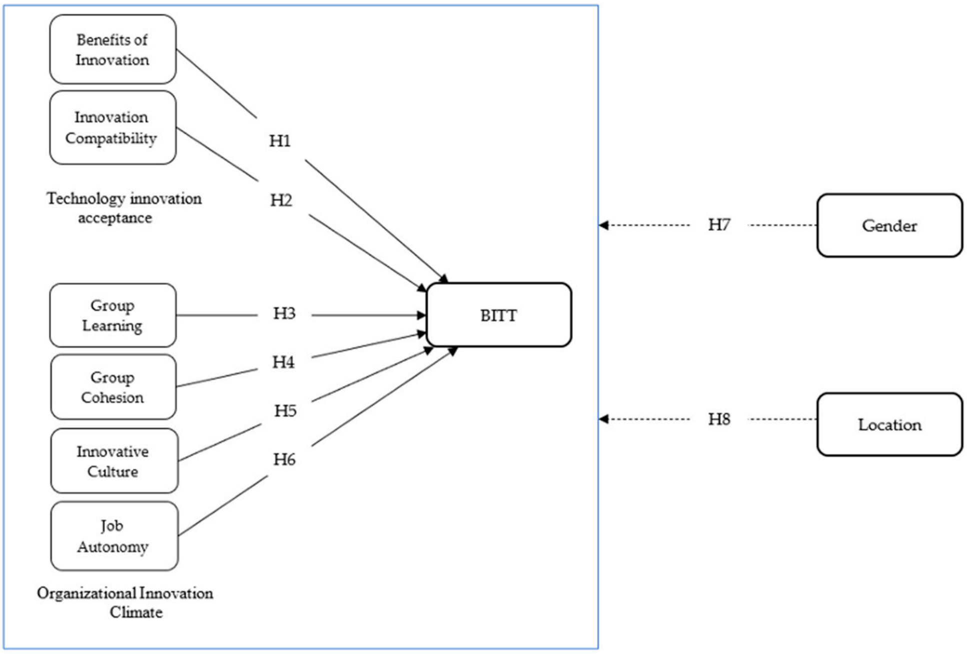

Figure 1. Proposed model.

H7. *Significant differences will emerge regarding all variables based on gender.*

H8. *Significant differences will emerge regarding all variables based on location.*

2. Materials and Methods

This study applied a survey focusing on factors affecting BITT among Indonesian primary school teachers. We validated a survey instrument based on prior studies to evaluate six hypotheses. The data analyses were performed using a structural model and MANOVA.

2.1. Instrumentation

Forty items for the survey instrument were adapted from previous research. Technology innovative acceptance was derived from Chou et al. [2], while the organizational innovation climate was derived from Amabile and Gryskiewic [18] and Bouckenooghe et al. [19], and BITT was derived from Chou et al. [2] and Teo [23] (Table 1). The survey items were chosen to meet the research objectives to explore factors affecting BITT. The items are unbiased, reliable, and legitimate, delivering comprehensive data that correctly reflect Indonesian primary school teachers' perspectives. The instrument was translated from English to Indonesian and from Indonesian to English, with a reverse translation [24].

Table 1. Main variable, source, constructs, and indicators.

Main Construct	Adapted from	Construct (34 Items)
Technology innovative acceptance	Chou et al. [2]	Benefits of innovation (BI1, BI2, BI3, BI4) Innovation compatibility (IC1, IC2, IC3, IC4)
Organizational innovation climate	Amabile and Gryskiewic [18]; Bouckenooghe, Devos, and Broeck [19]	Group learning (GL1, GL2, Gl3, GL4) Group cohesion (GC1, GC2, GC3, GC4) Innovative culture (I-Cul1, I-Cul2, I-Cul3, I-Cul4) Job autonomy (JA1, JA2, JA3, JA4)
BITT	Chou et al. [2]; Teo [23]	(BITT1, BITT2, BITT3, BITT4, BITT5, BITT6, BITT7, BITT8, BITT9, BITT10)

To validate the scale, we conducted discussions with ten teachers and five educational experts as part of the content and face validity procedures. Several indicators (n. 6) were eliminated during the procedures. This elimination was initiated due to the suggestions of experts and teachers regarding cultural and contextual distinctions. Additionally, we conducted back-translation to verify the indicators employed in this investigation. On a 5-point Likert scale (1 strongly disagree to 5 strongly agree), the instrument was piloted with 100 teachers. The pilot data exhibited a high level of reliability, as evidenced by the Cronbach's alpha value exceeding 700.

2.2. Data Collection

This research used quota sampling as a non-probability sampling technique. The researchers divided the population into mutually exclusive categories and picked participants from each segment based on a predetermined quota. Quota sampling was implemented to guarantee that subgroups of the population were adequately represented in the investigation. This approach is especially advantageous when the research objectives necessitate specific demographic characteristics, especially the gender and location of the respondents within this study context. Quota sampling is also efficient in terms of time and resources, as it allows us to achieve the desired sample size without the necessity of arbitrary selection. Moreover, it contributes to the study's generalizability and validity by capturing diverse perspectives. The data were collected from 868 primary school teachers, of whom 589 are females and 279 are males. Furthermore, 433 educators resided in urban areas, while the remaining 435 educators resided in rural areas. Teachers' teaching experience varies from less than five years to more than five years of experience. The survey employed an online application to gather the data over six months. We used manual checks in Microsoft Excel 365 to reduce the incidence of missing data during data collection [25].

2.3. Data Analysis

The data were evaluated for their normality via the evaluation of their skewness, kurtosis, and collinearity. For the measurement model, we used SmartPLS to calculate indicator loading, internal consistency reliability, convergent validity, and discriminant validity [25]. The structural model was reported through path coefficients, t and p values, effect sizes (f^2), the coefficient of determination (R^2), and predictive relevance (Q^2) values [25]. PLS-SEM is selected for its ability to handle complex models with small samples, non-normal data, and formative constructs, resulting in robust results in exploratory and theory-building research [25,26]. In addition to the structural model, the difference test was computed. The demographic information included gender and school location. Using MANOVA in SPSS 23.0, the difference was elaborated for F and p values. For all constructs, we identified outliers using box plots. For the univariate normality of each construct, the benchmark was the skewness and kurtosis values (−2 to +2) [26]. If the correlation is more than 0.90, multicollinearity emerges as an issue [26]. The missing data ranged from 0 to 0.5% per item. Table 2 provides the correlation matrix, skewness, kurtosis, means, and standard deviations for all constructs. The results obtained univariate normality, and no multicollinearity issues emerged [26].

Table 2. Correlation matrix, skewness, kurtosis, means, and standard deviations.

	Benefits of Innovation	Innovation Compatibility	Group Learning	Innovative Culture	Job Autonomy	Group Cohesion	BITT
Benefits of innovation	1	0.179 **	0.173 **	0.213 **	0.194 **	0.286 **	0.258 **
Innovation compatibility		1	0.118 *	0.241 **	0.196 **	0.146 **	0.221 **
Group learning			1	0.124 **	0.177 **	0.120 *	0.576 **
Innovative culture				1	0.248 **	0.270 **	0.271 **
Job autonomy					1	0.365 **	0.421 **
Group cohesion						1	0.397 **
BITT							1
Skewness	−0.093	−0.189	0.024	−0.223	0.035	0.080	0.110
Kurtosis	−0.726	−0.793	−1.139	−0.481	−0.423	0.041	0.188
Mean	5.2410	5.2889	5.3119	5.0310	4.9099	4.9488	5.0367
SD	0.90533	88920	0.94671	0.83248	0.88107	0.80247	0.62649

** ($p < 0.01$); * ($p < 0.05$).

3. Results

3.1. Measurement Model

We used SmartPLS 3.3 to assess the measurement model through PLS-SEM procedures. PLS-SEM is a simple application that estimates complex models [25]. Reflective indicator loadings, internal consistency reliability, convergent validity, and discriminant validity for the assessment of the measurement model are reported. The loading values should be >0.700 [25]. The loading-value item of <0.700 was subsequently dropped. As a result, five indicators were eliminated (BI4, IC4, GL4, JA4, and I-Cul4); twenty-nine items were retained. The internal consistency reliability in this study was calculated based on Cronbach's alpha and the composite reliability (CR). The threshold values of these two measurements range from 0.700 to 0.950 for satisfactory results. All of the constructs' alpha (0.766 and 0.889) and CR values (0.849 to 0.919) were satisfactory (Table 3). The results of loading and internal consistency reliability are satisfactory, resulting in reliable data for the proposed model [25].

Table 3. Reflective indicator loadings and internal consistency reliability.

Variable	Item	Load	α	CR	AVE
Benefits of innovation	BI1	0.938	0.830	0.880	0.712
	BI2	0.842			
	BI3	0.741			
BITT	BITT1	0.671	0.889	0.909	0.500
	BITT10	0.694			
	BITT2	0.690			
	BITT3	0.740			
	BITT4	0.744			
	BITT5	0.737			
	BITT6	0.657			
	BITT7	0.722			
	BITT8	0.715			
	BITT9	0.698			
Group cohesion	GC1	0.778	0.766	0.849	0.585
	GC2	0.799			
	GC3	0.754			
	GC4	0.725			
Group learning	GL1	0.855	0.789	0.877	0.706
	GL2	0.893			
	GL3	0.766			
Innovative culture	I-cul1	0.665	0.784	0.849	0.656
	I-cul2	0.843			
	I-cul3	0.903			
Innovation compatibility	IC1	0.835	0.813	0.889	0.727
	IC2	0.877			
	IC3	0.845			
Job autonomy	JA1	0.744	0.868	0.919	0.794
	JA2	0.950			
	JA3	0.962			

Convergent validity is the degree to which a variable group converges to measure a concept. In contrast, discriminant validity is the extent to which a construct differs from other constructs [25]. The convergent validity in the current study is measured by the assessment of average variance extracted (AVE); the values of the construct's AVE should be more than 0.50. All AVE values are >0.50, exceeding the threshold values (Table 3). Furthermore, HTMT was applied to assess the discriminant validity of the constructs [27]. HTMT is a novel approach to evaluate discriminant validity [25]. The HTMT is defined as a similarity measurement among latent variables. HTMT is efficient and straightforward to calculate, especially in the SmartPLS. HTMT is known to be the most robust statistical approach for identifying discriminant validity [25]. All scores are reported below 0.900 (from 0.042 to 0.624), which refers to the emergence of the model's discriminant validity (Table 4).

Table 4. HTMT ratio for discriminant validity (HTMT < 0.900) and model fit.

	BITT	BI	GC	GL	IC	I-Cul
BITT						
Benefits of innovation	0.131					
Group cohesion	0.567	0.148				
Group learning	0.624	0.062	0.491			
Innovation compatibility	0.044	0.046	0.042	0.066		
Innovative culture	0.090	0.067	0.056	0.042	0.129	
Job autonomy	0.084	0.044	0.094	0.080	0.455	0.086

The PLS-SEM procedure suggests reporting the standardized root means square residual (SRMR) at a 95% bootstrap quantile for the fit model. The model emerges when the number of free parameters equals the number of variances [25]. SRMR is categorized as the sole criterion for the model fit in PLS-SEM procedures. Furthermore, Hair et al. [25] also proposed dULS (squared Euclidean distance) and d_G (geodesic distance) for the model fitness index. dG and dULS are defined as two distance measurements that link in more than one way to compute the discrepancy between two matrices. Table 4 indicates that the dG and the dULS reflect satisfactory values of 1.630 and 0.520, respectively. The SRMR is 0.056, below 0.08, implying the good model fit of the data (Table 5). The valid and reliable data can be downloaded at: https://figshare.com/s/af9708cd0053ead112bd (Supplementary Materials).

Table 5. Model fit.

	Estimated Model
SRMR	0.056
d_ULS	1.360
d_G	0.520
Chi-Square	2.786

3.2. Structural Model

We examined multicollinearity by informing the variance inflation factor (VIF) before reporting the structural model. The VIF was used to report the test for possible multicollinearity issues. VIF values that range from 1.009 to 1.048 support proper construct validity with no issue with multicollinearity. The values fall significantly below the minimum threshold of five [27]. Furthermore, the structural model assessment was conducted [25]. Cut-off values for statistical significances (β, t value, and *p*-value), effect sizes (f^2), the coefficient of determination (R^2), and predictive relevance (Q^2) were devised. A minimum t value of 1.650 at $p \leq 0.50$ was implemented [25]. Similarly, the effect sizes symbolized with f^2 values of 0.35, 0.15, and 0.02 indicate that the exogenous constructs have a large, medium, and small effect, respectively. R^2 values of 0.75, 0.5, and 0.25 reflect substantial, moderate, and weak scores, respectively [25]. Furthermore, Q^2 values higher than zero for specific endogenous constructs indicate satisfactory predictive accuracy [28]. We applied consistent PLS bootstrapping of 5000 subsamples to obtain the results of statistical significance, f^2, and R^2 ([26], while Q^2 computation was carried out through SmartPLS' blindfolding button [27]. Four relationships are significantly related to the six proposed hypotheses (Table 6 and Figure 2). Regarding the relationships, group learning has been indicated to have the most substantial significant relationship with BITT (β = 0.404; t = 12.037; $p > 0.001$), followed by the relationship between group cohesion and BITT (β = 0.307; t = 8.517; $p > 0.001$). The weakest significant relationships emerge between benefits of innovation and BITT (β = −0.079; t = 2.816; $p > 0.05$) and between innovative culture and BITT (β = −0.075; t = 2.599; $p > 0.05$). The results confirmed hypotheses 1, 3, 4, and 5. However, two of the six hypotheses are reported to be insignificant. The insignificant relationships emerge between the benefits of innovation and BITT (β = 0.025; t = 0.799; $p = 0.424$), as well as job autonomy and BITT (β = 0.026; t = 0.915; $p = 0.360$). Like the path coefficients, the results of the inner (structural) model in Table 6 reveal that group learning has the most significant positive effect size on BITT ($f^2 = 0.224$). Group cohesion ($f^2 = 0.127$), benefits of innovations ($f^2 = 0.010$), and innovative culture ($f^2 = 0.009$) have weak positive influences on BITT [25].

Table 6. Bootstrapping results: VIF, β, t-value, *p*-value, f^2, and decision.

	Path	VIF	β	t-Value	*p*-Value	f^2
H1	Benefits of innovation -> BITT	1.024	−0.079	2.816	0.005 *	0.010
H2	Innovation compatibility -> BITT	1.180	0.025	0.799	0.424	0.001
H3	Group learning -> BITT	1.178	0.404	12.037	0.000 **	0.224
H4	Group cohesion -> BITT	1.205	0.307	8.517	0.000 **	0.127
H5	Innovative culture -> BITT	1.026	−0.075	2.599	0.009 *	0.009
H6	Job autonomy -> BITT	1.177	0.026	0.915	0.360	0.001

** ($p < 0.01$); * ($p < 0.05$).

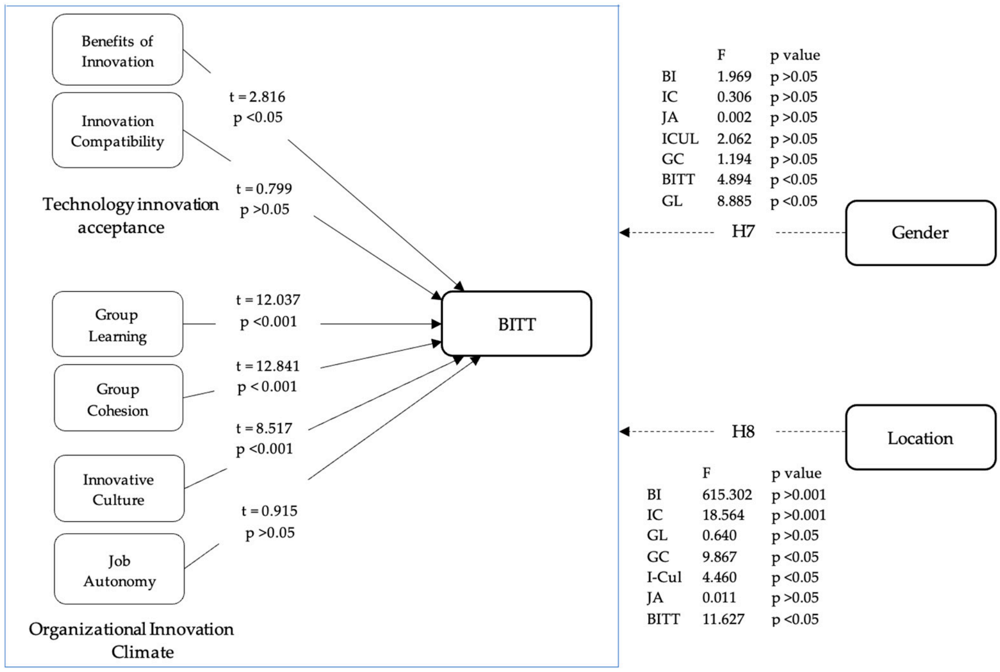

Figure 2. Final model.

The coefficient of determination (R^2) was also assessed in this study. R^2 was reported to encompass the variance degree elaborated by all five exogenous constructs within this research. The computation result for the value of R^2 in this study is 0.381, revealing that the variance degree is at a moderate level for BITT. Therefore, the results recommend that all exogenous constructs represent positive explanations of the variance in BITT that can be defined as meaningful [25]. For Q^2, the computation through blindfolding on the SmartPLS 3.3 shows acceptable predictive accuracy for the endogenous variable (Q^2 = 0.183, BITT) based on the suggested threshold proposed by previous seminal research [28] to determine models' predictive performance.

3.3. MANOVA

Table 7 shows the results of the test of the between-subjects effect included in MANOVA. When F values are more significant than 4 and *p* values are smaller than 0.5, the differences are significant. Based on gender, the significant differences were only found in two dependent variables, namely BITT (F = 9.412; $p < 0.05$) and group learning (F = 8.885; $p < 0.05$). The other variables show insignificant differences. On the other hand, most variables were found to be very significantly different based on location, for example, benefits of innovation (F = 615.302; $p < 0.001$), innovation compatibility (F = 18.564; $p < 0.001$), and BITT (F = 11.627; $p < 0.001$). Two variables are not positively different regarding location, namely job autonomy (F = 0.136; $p > 0.05$) and group learning (F = 0.540; $p > 0.05$).

Table 7. Differences based on gender and location.

Variable	Mean (Male; n. 279)	Mean (Female; n. 589)	F	*p*-Value
BI	4.0036	3.9140	1.969	0.161
IC	3.7455	3.7204	0.306	0.581
JA	2.8495	2.8466	0.002	0.964
ICUL	4.3536	4.2869	2.062	0.151
GC	3.6013	3.6558	1.194	0.275
BITT	3.6082	3.7042	4.894	0.027
GL	3.7730	3.9247	8.885	0.003
Variable	**City; n. 433**	**Village; n. 435**	**F**	***p*-value**
BI	4.5104	3.3778	615.302	0.000
IC	3.8191	3.6383	18.564	0.000
JA	2.8445	2.8506	0.011	0.918
ICUL	4.2625	4.3540	4.460	0.035
GC	3.5652	3.7109	9.867	0.002
BITT	3.6044	3.7421	11.627	0.001
GL	3.8568	3.8950	0.640	0.424
BI	4.5104	3.3778	615.302	0.000

4. Discussion

The scale resulting from this study can be altered for future scholars interested in similar research areas. In this study, a structural model of two main constructs (technology innovation acceptance and organizational innovation climate) as exogenous variables was included in the model to predict BITT. Overall, the study's empirical data analysis for exogenous and endogenous variables aligns well with the structural model. The results show that technology innovation acceptance has a lower predictive power than an organizational innovation climate. Similar results were reported by Abdullah and Ward [29], Lau and Yuen [30], Obiri-Yeboah et al. [31], and Cao et al. [32]. Specifically, based on the study's findings, analyzed using PLS-SEM, one variable of technology innovation acceptance (innovation compatibility) failed to predict BITT; nevertheless, the benefits of innovation significantly influence BITT [2]. The findings of the study indicate that when Indonesian teachers have a high perception of the usefulness of creative practices, they are more likely to engage in innovative behaviors, particularly when it comes to incorporating technology into their teaching. In addition to serving as a motivator, this impression of usefulness encourages educators to investigate new approaches and instruments that can improve students' educational experiences. When they become aware of the advantages, which include increased student engagement, personalized learning, and more effective classroom management, they develop a greater sense of self-assurance and become more aggressive in adopting technology. Cultivating a favorable impression of the value of innovation among educators might result in the more efficient and broad application of technological tools in educational settings across Indonesia.

In addition, three hypotheses (group learning, group cohesion, and innovative culture) out of four hypotheses about the organizational innovation climate significantly predicted BITT. However, one of the variables (job autonomy) fails to significantly influence BITT. Teachers' limited freedom to teach could explain the insignificant relationship with BITT [29]. Teachers might still strictly follow the curriculum and other related policies when teaching using technology [30]. In the current context, the organizational innovation climate has more predictive power than technology innovation acceptance towards BITT. The innovation climate plays a crucial role in enhancing creative teaching and promoting positive achievement in education [14], particularly during the teaching process. The current findings confirm the results of Hernández-Ramos et al. [33], who suggested that the innovation climate of an organization produces individual creativity. Furthermore, Obiri-Yeboah et al. [31] reported that positive attitudes toward the use of technology improved technology integration in education. Teachers may face barriers to technology integration for teaching, such as a lack of technology skills, limited access to technology, resistance to change, inadequate training and support, increased workload, concerns about student engagement, and privacy and security concerns [31,32]. Inadequate devices or inadequate Internet connectivity also impede the effective utilization of technology. Furthermore, adoption may be hindered by resistance to change from conventional educational methods. Teachers may lack the confidence or preparedness to employ new tools due to inadequate training and support from academic institutions. Additionally, the heightened burden associated with integrating technology into lesson plans and the learning process can be overwhelming. Teachers may also harbor reservations regarding the sustained engagement of students in a digital environment, as they anticipate distractions or diminished interaction. It is essential for schools and other related stakeholders to provide teachers with the necessary resources and support to overcome these barriers and effectively integrate technology into their teaching during pandemic events.

Most variables are not significantly different based on gender, except for BITT and group learning. The findings could be triggered by the 21st-century gender equality that has transformed Indonesia into a country where technology integration in education is not different between male teachers and female teachers, referring to the equality of access and use of technology [6]. Contradicting the current study results, Ramirez-Correa et al. [10] found that gender differences (between males and females) as a demographic reference in technology integration were significant. They found that males had a more considerable path coefficient than females on factors affecting the use of e-learning in education [10]. Further investigation is required for more varieties of demographic information. On the other hand, the MANOVA indicates that the mean scores between respondents' school locations are significantly different regarding most variables. This information proves that locations are vital backgrounds to differences in technology integration, supporting prior studies on educational technology [6,10]. Previous studies have shown that contextual factors influence technology incorporation in different locations. Understanding the local context is crucial to implementing technology improvements in education since it ensures that policies are suited to each area's demands and challenges [21,22].

Limitation and Future Studies

The study encountered several limitations that necessitate further investigation. Initially, the model was constructed using data from 868 respondents, which may restrict the generalizability of the results. Consequently, a more comprehensive comprehension of the phenomena would be achieved by increasing the sample size in future studies. Furthermore, the conclusions of this investigation were restricted to Indonesian primary school instructors. Future research results should be more applicable by incorporating a more diverse cohort of teachers from various educational levels, cultural contexts, and geographical regions. Additionally, the investigation concentrated on cross-sectional and correlational research methodologies, which offer significant insights but which have a restricted ability to confirm causality. The inclusion of qualitative methods, such as interviews or focus groups, in the research approach could provide a more profound comprehension of the underlying motivations, attitudes, and experiences. Experimental designs may also facilitate a more definitive identification of causal relationships. Finally, it would be advantageous to investigate a variety of contexts and scenarios, thereby enhancing comprehension of the subject matter. The proposed enhancements could significantly improve the validity, reliability, and applicability of future research in this field.

5. Conclusions

We need to use digital technology in various ways to deal with the process of learning through digital resources, which is frequently an unfamiliar experience for both teachers and the students they teach. BITT has been provided with empirical evidence because of this investigation. The characteristics that predict BITT among Indonesian teachers throughout their teaching sessions are the focus of this study, which explores those factors.

According to the findings, one of the elements that influence the adoption of technological innovations was inconsequential in predicting BITT. Significant contributions were made by three out of the four elements that comprised the organizational innovation climate. Regarding BITT, instructors are influenced by their peers, with group learning being the most significant component. This phenomenon may result from the social trait of respecting the opinions of others, which is common in Eastern cultures, such as Indonesia.

Supplementary Materials: The following supporting information can be downloaded at: https://figshare.com/s/af9708cd0053ead112bd (accessed on 24 September 2024).

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