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Behavioral Switching Model To Hybrid Learning Based on Push Pull Mooring Framework

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ABSTRAK

Pandemi Covid-19 telah mengakibatkan pergeseran pembelajaran berbasis hybrid. Tujuan dari penelitian ini adalah untuk menganalisis bagaimana efek mooring push-pull mampu meningkatkan transisi perilaku siswa ke pembelajaran hybrid selama pandemi Covid-19. Penelitian ini menggunakan pendekatan kuantitatif. Populasi penelitian adalah seluruh mahasiswa aktif Fakultas Ekonomi. Sampel yang digunakan sebanyak 146 responden, dengan teknik non probability sampling. Teknik pengumpulan data adalah metode angket online dengan skala interval setuju (skala 7) sampai tidak setuju (skala 1). Teknik analisis data berdasarkan Structural Equation Modeling Partial Least Square (SEM PLS) dengan menggunakan program WarpPLS 5.0. Hasil penelitian menunjukkan bahwa push effect, pull effect, mooring effect, decision self efficacy, dan motivation and intention switching berpengaruh terhadap switching behavior. Sedangkan push and pull effect tidak berpengaruh terhadap switching behavior melalui motivasi dan intention to switch dan self-efficacy keputusan, berbeda dengan mooring effect yang berpengaruh signifikan. Temuan dari penelitian ini adalah pembelajaran hybrid belum mampu meningkatkan kinerja siswa dibandingkan pembelajaran offline, sehingga perilaku siswa untuk beralih ke pembelajaran hybrid masih perlu ditingkatkan.

ABSTRACT

The Covid-19 pandemic has resulted in a shift in hybrid-based learning. The purpose of this study is to analyze how the push-pull mooring effect is able to increase student behavior transition to hybrid learning during the Covid-19 pandemic. This study uses a quantitative approach. The research population is all active students of the Faculty of Economics. The sample used was 146 respondents, with non-probability sampling technique. The data collection technique was an online questionnaire method with an interval scale of agree (scale 7) to disagree (scale 1). Data analysis technique was based on Structural Equation Modeling Partial Least Square (SEM PLS) using WarpPLS 5.0 program. The results showed that the push effect, pull effect, mooring effect, decision self efficacy and motivation and intention switching had an effect on switching behavior. While the push and pull effects have no effect on switching behavior through motivation and intention to switch and decision self-efficacy, in contrast to the mooring effect which has a significant effect. The findings of this study are that hybrid learning has not been able to improve student performance than offline learning, so the student behavior to switch to hybrid learning still needs to be improved.

1. INTRODUCTION

The Covid-19 pandemic has resulted in various changes, including the transition from conventional learning to online-based learning, which has now shifted to hybrid learning. Students in particular, are faced with changes in online digital education, so that these events and existing technological advances trigger a person's behavior to switch to adapt to existing conditions (Firth et al., 2019; Oerther & Peters, 2020). This unique transformation will become a necessity for students during the Covid 19 crisis, to switch to online and hybrid learning systems, such as economics learning which requires students to develop their skills and competencies for future needs (Díaz, 2020; Sindi et al., 2021). However, the gap phenomenon of research at the Faculty of Economics, Universitas Negeri Semarang (UNNES) shows conditions that are not suitable. The results of observations show that student behavior in online learning, especially synchronous learning shows their low participation by disabling video cameras and even when learning is taking place they are not in place and only activate the zoom media. The same thing happens in hybrid learning, where students who are face-to-face (offline) are more active than students who follow online. The results of interviews with students stated that their reluctance to be

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active in synchronous learning was due to network constraints and low motivation to learn because they were getting bored with online-based learning. This empirical fact is reinforced by previous research that online learning (synchronous and asynchronous) has weaknesses such as a sense of community and low student involvement in learning (Cunningham, 2014; Farrell & Brunton, 2020). The research gap emerged when previous study suggested that online learning has more advantages in contributing to direct feedback and motivation (N. S. Chen et al., 2005). Other state that online learning is not limited by time and more flexibility (Ebner & Gegenfurtner, 2019; Martin et al., 2012). Online learning offers wider access to learning resources and opportunities anytime and anywhere through technology (Antee, 2021; Stewart et al., 2011).

Regarding the transition to hybrid-based learning, previous researchers have developed many research model frameworks to explain the tendency of users to adopt technology based on various factors (Y. H. Chen & Keng, 2019; Cheng et al., 2019; Hsu, 2014; Lin et al., 2021). The intention to switch to an online learning platform towards technology adoption is explained through the theory of Push-Pull Mooring (PPM) (Lin et al., 2021). Push factors influence users to stay away from current technology, while pull factors attract users towards newer technologies (Hsu, 2014). While the mooring factor is a variable that facilitates or limits the intention to switch users towards technology adoption (Cheng et al., 2019). When students switch to online learning service providers, the change is basically a kind of switching behavior, so the theory "Push-Pull Mooring (PPM)" can be used as a theoretical framework to understand existing migration patterns (Y. H. Chen & Keng, 2019).

Regarding the intention to switch, several previous studies used the Push-Pull Mooring (PPM) framework to explain switching behavior (Hou & Shiau, 2020; Xu et al., 2014). Previous study stated that the Push-Pull Mooring framework does not mandate a fixed variable for the effects of push, pull and mooring (Bansal et al., 2005). By using this PPM, we only need to consider the uniqueness of the research background, and then determine the push, pull and mooring factors of various topics, which are more appropriate to explore the transfer of learning from conventional face-to-face to online learning (Su & Wu, 2020; Zhang et al., 2012), and their respective alternative appeals (Susanty et al., 2020; Tang & Chen, 2020). However, switching intention is still influenced by many factors namely socializing, enjoyment, system quality of the social networking sites (SNS), customer service satisfaction, which is a push effect, and alternative attractiveness, the influence of coworkers, critical mass, which is a pull effect.

Responding to the current hybrid learning switching behavior, researchers refer to previous study which use perceived security risk (PSR), learning convenience (LC) and service quality (SQ) as the main factors in the push effect, and instructor attitudes (IA), technology compatibility (TC), perceived ease of use (PEU), and perceived usefulness (PU) are the main factors in the pull effect (Lin et al., 2021). While the mooring effect, this study tries to understand the influence of habits (H) and the costs incurred by students to switch (switching cost/SC), and see the effect of these three variables on the behavior of switching to hybrid learning. Furthermore, the researcher considers decision self efficacy (DSE) as well as motivation and intention to switch (MIS) as mediating variables. In general, it is observed that students (as technology adopters) examine and evaluate their choices. Students also evaluate how easy it is for them to integrate the various facilities available in online learning technology (Joshi et al., 2021; Sajjad et al., 2020). This factor is described in the research as decision self-efficiency. Meanwhile, the conceptualization of motivation and intention to switch is described as a psychological tendency of students to become more determined to participate in online learning, and improve the quality of their learning (Beqiri et al., 2009; Hodges et al., 2020; Reeve, 2012). Thus, students become more dedicated to spending time in online learning.

Finally, the authors consider switching behavior (SB) as the dependent variable, arguing that the time, effort and attention they previously devoted to classroom learning are equally provided in online learning. As such, it is an important, existential and substantive shift towards online learning. The purpose of this study is to analyze how the push-pull mooring effect is able to increase student behavior transition to hybrid learning during the Covid-19 pandemic. Analyzing how strong the determination of the push-pull mooring effect, decision self-efficacy and motivation and intention to switch determine student behavior switching.

2. METHODS

This study develops a conceptual model of switching behavior factors to hybrid economics learning in universities, with a quantitative approach. This study uses a quantitative approach, with the design of this study is an associative clause design, to analyze the relationship and how one variable affects other variables. The location of this research is the Faculty of Economics, Universitas Negeri

Semarang (UNNES), with a population of all active students of the Faculty of Economics, UNNES as many as 6,516 people.

Determination of the sample was carried out using non-probability sampling with a sample size of 146 respondents (referring to the adequacy of the data in the structural analysis. Data were collected by using a questionnaire with an interval scale of Agree (scale 7) to Disagree (scale 1). Questionnaires are made online via google form, then distributed to students when they finish their lectures. After the data is collected from the field, further processing is carried out (editing, namely checking the completeness and examining the data that has been collected, especially from the completeness of the answers,and converting data), so that the widely distributed data in the questionnaire items can be made more concise and simpler.

The data analysis technique used is based on Structural Equation Modeling Partial Least Square (SEM PLS) using the WarpPLS 5.0 program. Data analysis techniques in this study consisted of: *first,* descriptive statistical analysis; to determine the minimum, maximum, average and standard deviation values in each of the variables studied. *Second,* analysis of validity and reliability; to determine the level of validity and constancy of an instrument. An instrument is said to be valid if the convergent validity value of the loading factor CFA (Confirmatory Factor Analysis) is above 0.6, and seen from the discriminant validity AVE (Average Variance Extracted) above 0.5. Meanwhile, for reliability testing using a composite reliability value above 0.7. *Third,* inferential statistical analysis using Partial Least Square Structural Equation Modeling (SEM) technique, namely model conceptualization; determine the algorithm analysis method; determine the resampling method, describe the path diagram; evaluation of the Goodness of Fit (GoF) criteria, in order: data normality, outliers, multicollinearity and singularity; evaluate and estimate the inner and outer models, to know the value of t statistics, while to evaluate the model using Q2; report the results of the analysis.

3. RESULT AND DISCUSSION

Results

The elaboration of the results of this study begins with descriptive statistical analysis, evaluation of the measurement and structural model, then hypothesis testing. Descriptive statistical analysis was calculated from the minimum, maximum, mean, and standard deviation values. The results of the descriptive statistical analysis are presented in **Table 1**.

Table 1. Descriptive Statistical Analysis Results

Variable	Dimension	Min	Max	mean	Std. Deviation
GPA		3	3.95	3.61	0.17
Push Effect	Perceived security risk	7	21	16.74	3.10
	Learning convenience	9	28	21.60	4.06
	Service quality	9	21	16.12	3.06
Pull Effect	Instructor attitude	4	21	16.40	3.62
	Technology compatibility	4	21	15.94	3.88
	Perceived usefulness	3	21	14.82	4.60
	Perceived ease of use	8	35	26.22	5.57
Mooring Effect	Habit	3	21	15.98	3.65
	Swithing cost	9	28	21.84	3.93
Decision Self Efficiency		7	21	15.88	2.97
Motivation and Intention Switching		9	28	21.51	4.09
Switching Behavior		3	21	14.47	4.01

Based on the results of the descriptive analysis presented in Table 1, it can be seen that the data used has a good data variance. This is evidenced by the existence of a fairly large range of the average value of each dimension on each variable with the standard deviation value of that dimension. Where the GPA has an average value of 3.61, it shows that the average respondent's learning outcomes are classified as very good. In the Push Effect variable, there are three dimensions, namely Perceived security risk, Learning Convenience and Service quality, from these three dimensions learning conveinance is the dimension with the highest average of 21.60. While the other two dimensions, namely Perceived security risk and Service quality, each have an average value of 16.74 and 16.12.

The Pull Effect variable in this study is proxied by four dimensions, namely Instructor attitude, Technology compatibility, Perceived usefulness, and Perceived ease of use, with each having an average value of 16.40; 15.94; 14.82; and 26.22. While the Mooring Effect is measured by two dimensions, namely habit and switching cost with each showing an average value of 15.98; and 21.84. Meanwhile, the variables for Decision Self Efficiency, Motivation and Intention Switching, Switching Behavior are not divided into dimensions and are only measured based on indicators that interpret these variables with each average value of 15.88; 21.51; and 14.47.

Evaluation of the Measurement Model (Outer Model)

Convergent validity is based on the value of the loading construct which can be seen through the combined loading cross-loading output. If the value of the loading construct is greater than 0.7 then it is declared to meet the requirements of convergent validity, while if it does not meet 0.7 then the construct must be dropped from the analysis model. Furthermore, it can be said to be significant if the p-value is less than 0.5. Variable construct loading value is show in Table 2.

Table 2. Variable Construct Loading Value

Variable	Dimension	Indicator	Loading Value	p-value	Information
Push Effect	Perceived security risk	PSR1	0.878	<0.001	Meet convergent validity
		PSR2	0.675	<0.001	Meet convergent validity
		PSR3	0.878	<0.001	Meet convergent validity
	Learning convenience	LC1	0.571	<0.001	Meet convergent validity
		LC2	0.750	<0.001	Meet convergent validity
		LC3	0.800	<0.001	Meet convergent validity
		LC4	0.663	<0.001	Meet convergent validity
	Service quality	SQ1	0.748	<0.001	Meet convergent validity
		SQ2	0.684	<0.001	Meet convergent validity
		SQ3	0.889	<0.001	Meet convergent validity
Pull Effect	Instructor attitude	IA1	0.860	<0.001	Meet convergent validity
		IA2	0.802	<0.001	Meet convergent validity
		IA3	0.826	<0.001	Meet convergent validity
	Technology compatibility	TC1	0.795	<0.001	Meet convergent validity
		TC2	0.889	<0.001	Meet convergent validity
		TC3	0.845	<0.001	Meet convergent validity
	Perceived usefulness	PU1	0.830	<0.001	Meet convergent validity
		PU2	0.844	<0.001	Meet convergent validity
		PU3	0.813	<0.001	Meet convergent validity
	Perceived ease of use	PEU1	0.815	<0.001	Meet convergent validity
		PEU2	0.808	<0.001	Meet convergent validity
		PEU3	0.789	<0.001	Meet convergent validity
		PEU4	0.783	<0.001	Meet convergent validity
		PEU5	0.771	<0.001	Meet convergent validity
Mooring Effect	Habit	H1	0.864	<0.001	Meet convergent validity
		H2	0.923	<0.001	Meet convergent validity
		H3	0.830	<0.001	Meet convergent validity
	Swithing Cost	SC1	0.864	<0.001	Meet convergent validity
		SC2	0.812	<0.001	Meet convergent validity
		SC3	0.797	<0.001	Meet convergent validity
		SC4	0.664	<0.001	Meet convergent validity
Decision Self Efficiency		DSE1	0.845	<0.001	Meet convergent validity
		DSE2	0.889	<0.001	Meet convergent validity
		DSE3	0.869	<0.001	Meet convergent validity
Motivation and Intention Switching		MIS1	0.725	<0.001	Meet convergent validity
		MIS2	0.886	<0.001	Meet convergent validity
		MIS3	0.902	<0.001	Meet convergent validity
		MIS4	0.819	<0.001	Meet convergent validity
Switching Behavior		SB1	0.906	<0.001	Meet convergent validity
		SB2	0.917	<0.001	Meet convergent validity
		SB3	0.909	<0.001	Meet convergent validity

Source: Processed WarpPLS 7.0 output, 2022

Based on Table 2, it can be seen that all indicators in each dimension of the push effect, pull effect, mooring effect, decision self-efficacy, motivation and intention switching, and switching behavior have been proven to meet the requirements of convergent validity. This is evidenced by the p-value of each indicator which has a value of <0.05 with a loading value of more than 0.7 although there are several indicators that are less than 0.7, namely the PSR2, LCI, LC4, SQ1, and CS4 indicators which each has a loading value of 0.675; 0.571; 0.663; 0.684; and 0.664. However, these five indicators can still be maintained and are said to be feasible to use in the research model, because in addition to using the loading construct value, the convergent validity measurement is also carried out by looking at the AVE (average variance extracted) value. The AVE value used for evaluating convergent validity has criteria that must be met, namely AVE> 0.50. The AVE value can be seen in the Output Latent Variable Coefficients Table in Table 3.

Table 3. Output Latent Variable Coefficients

	PushEf	PullEff	MoorEff	DSE	MIS	SB
Avg. var. Extract	0.578	0.672	0.682	0.753	0.698	0.829

Based on Table 3, it is known that PushEff, PullEff, MoorEff, DSE, MIS, and SB each have an AVE value of 0.578; 0.672; 0.682; 0.753; 0.698; 0.829. The six values show greater than 0.5 so it can be said that based on the AVE value, the four variables have met convergent validity. Discriminant Validity can be done by looking at the criteria for the square root of AVE which is in the diagonal column and is bracketed. This value must be higher than the correlation between latent variables in the same column. The results of the AVE quadratic calculation can be seen in Table 4.

Table 4. Correlations Among Latent Variables

	PushEf	PullEff	MoorEff	DSE	MIS	SB
PushEf	(0.760)	0.662	0.542	0.584	0.399	0.216
PullEff	0.662	(0.820)	0.785	0.740	0.524	0.510
MoorEff	0.542	0.785	(0.826)	0.802	0.688	0.586
DSE	0.584	0.740	0.802	(0.868)	0.637	0.573
MIS	0.399	0.524	0.688	0.637	(0.836)	0.564
SB	0.216	0.510	0.586	0.573	0.564	(0.911)

Table 4. shows that the discriminant validity criteria have been met, which is indicated by the square root of the AVE of each variable being greater than the correlation coefficient between constructs in each variable, wherePushEff, PullEff, MoorEff, DSE, MIS, and SB all have AVE square root values of 0.760; 0.820; 0.826; 0.868; 0.836; and 0.911 and higher than the correlation between latent variables in the same column. Therefore, it can be said that it has met the requirements of discriminant validity. This test can be measured by two criteria, namely the value of composite reliability and Cronbach alpha. A variable can be said to be reliable if the value of composite reliability is > 0.70. The results of the output latent variable coefficients can be seen in Table 5.

Table 5. Output Latent Variable Coefficients

	PushEf	PullEff	MoorEff	DSE	MIS	SB
Composite Reliable	0.931	0.966	0.937	0.901	0.902	0.936

Source: Processed WarpPLS 7.0 output, 2022

Based on Table 5, it is known that the composite reliability valuePushEff, PullEff, MoorEff, DSE, MIS, and SB have a composite reliability value of 0.931; 0.966; 0.937; 0.901; 0.902; 0.936. The six composite reliability values are > 0.70, so it can be concluded that all variables have met the composite reliability criteria.

Evaluation of the Structural Model (Inner Model)

The evaluation of the structural model of the inner model is seen by looking at the fit and quality indices model, the R-squared and Q-squared values. After processing the data with the multiple mediating effects model, the fit indices and p-values model is produced as shown in Table 6.

Table 6. Model Fit And Quality Indices

Model Fit & Quality Indices	***Index***	***p-value***	***Criteria***	**Information**
*Average path coefficient*APC	0.265	P=0.001	P<0.05	Received
*Average Rsquared*ARS	0.603	P=0.001	P<0.05	Received
*Average adjusted Rsquared*AARS	0.591	P=0.001	P<0.05	Received
*Average block VIF*AVIF	2,618	*acceptable if* <=5, ideally <=3.3		*ideally*
*Average full collinearity VIF*AFVIF	2,893	*acceptable if* <=5, ideally <=3.3		*ideally*
*Tenenhaus GoF*GoF	0.651	*small*>= 0.1, medium >= 0.25, large >= 0.36		*Large*
*Sympson's paradox ratio*SPR	1,000	*acceptable if* >=0.7, ideally = 1		Received
*R-squared contribution ratio*RSCR	1,000	*acceptable if* >=0.9, ideally = 1		Received
*Statistical suppression ratio*SSR	1,000	*acceptable if* >=0.7		Received
*Nonlinear bivariate causality direction ratio*NLBCDR	1,000	*acceptable if* >=0.7		Received

Based on Table 6, the fit and quality indices model, the values obtained from the ten criteria have been met, so it can be said that the model has met the model fit requirements. The image of the estimation result of the indirect effect model is shown in **Figure 1**.

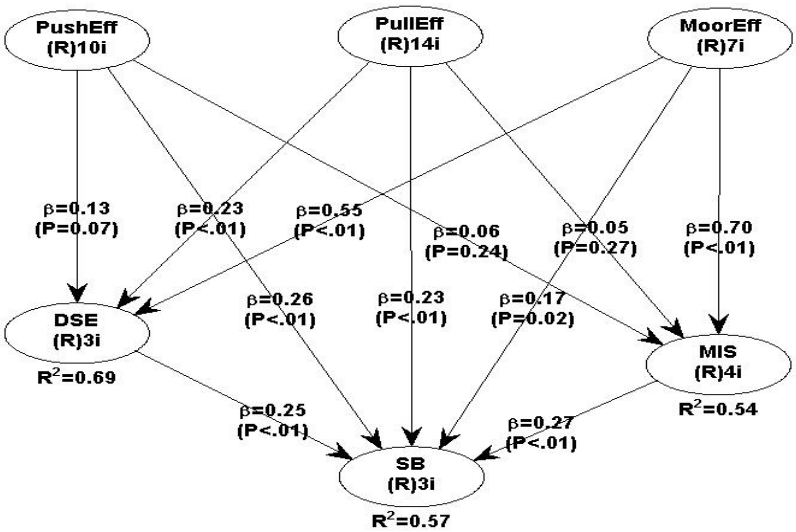

Figure 1. Indirect Effect Model Test Results

Based on Figure 1, show the indirect effect model testing of the structural model is done by looking at the R-squared which is a goodness fit model test. The results show the R-square value on the variablePush Effect, Pull Effect, Moor Effect on Switching Behavior, through Decision Self Efficacy and Motivation and Intention Switching is 0.57, meaning that the exogenous latent variables in this study are able to influence Switching Behavior by 0.57.

Q-squared is used to assess predictive validity or relevance of a set of latent predictor variables on criterion variables. The model with predictive validity must have a Q-Squared value > 0. The following (Table 7) is a table of latent variable coefficients that describes the Q-Squared value of the latent predictor variable on the criterion variable. Based on the output latent variable coefficients in **Table 7** shows the value of the Q-Squared variableSBis 0.457. This means that the research model has predictive relevance because it has a Q-Squared of more than zero.

Table 7. Output Latent Variable Coefficient Describing Q-Squared

	PushEf	**PullEff**	**MoorEff**	**DSE**	**MIS**	**SB**
Q-Squared				0.693	0.491	0.457

Hypothesis Test Results

The correlation between constructs is measured by looking at the path coefficient and the level of significance. The level of significance used in this study is 0.05 or 5%. The results of hypothesis testing can be seen in Table 8.

Table 8. Research Hypothesis Test Results

No	Hypothesis	Hypothesis Test Results			
		Coefficient	Sig.	α	Information
1.	Push Effec t (PushEff) has a significant effect on Switching Behavior (SB)	0.259	<0.001	0.05	Received
2.	Pull Effect (PullEff) has a significant effect on Switching Behavior (SB)	0.232	0.003	0.05	Received
3.	Mooring Effect (MoorEff) has a significant effect on Switching Behavior (SB)	0.168	0.025	0.05	Received
4.	Decision Self Efficacy (DSE) has significant effect on Switching Behavior (SB)	0.253	0.001	0.05	Received
5.	Motivation and Intention to Switching (MIS) has a significant effect on Switching Behavior (SB)	0.267	<0.001	0.05	Received
6.	Push Effect (PushEff) has a significant effect on Motivation and Intention to Switching (MIS)	0.062	0.237	0.05	Rejected
7.	Pull Effect (PullEff) has a significant effect on Motivation and Intention to Switching (MIS)	0.053	0.271	0.05	Rejected
8.	Mooring Effect (MoorEff) has a significant effect on Motivation and Intention to Switching (MIS)	0.704	<0.001	0.05	Received
9.	Push Effect (PushEff) has a significant effect on Decision Self Efficacy (DSE)	0.129	0.066	0.05	Rejected
10.	Pull Effect (PullEff) has a significant effect on Decision Self Efficacy (DSE)	0.232	0.003	0.05	Received
11.	Mooring Effect (MoorEff) has a significant effect on Decision Self Efficacy (DSE)	0.554	<0.001	0.05	Received
12.	Push Effect (PushEff) has a significant effect on Switching Behavior (SB) through Motivation and Intention to Switching (MIS) and Decision Self Efficacy (DSE) as mediating variables	0.049	0.286	0.05	Rejected
13.	Pull Effect (PullEff) has a significant effect on Switching Behavior (SB) through Motivation and Intention to Switching (MIS) and Decision Self Efficacy (DSE) as mediating variables	0.073	0.201	0.05	Rejected
14.	Mooring Effect (MoorEff) has a significant effect on Switching Behavior (SB) through Motivation and Intention to Switching (MIS) and Decision Self Efficacy (DSE) as mediating variables	0.328	<0.001	0.05	Received

Hypothesis testing in Table 8 shows that of the 14 hypotheses proposed, there are 9 accepted hypotheses, while 5 hypotheses are rejected. The rejected hypothesis is the direct effect of the variablepush and pull effect on motivation and intention to switch (MIS), and push effect on decision self, as well as the indirect effect of push and pull effect on switching behavior through motivation and intention to switch and decision self efficacy as mediating variables. The accepted hypothesis was identified that 9 hypotheses had a significant effect, namely H1, H2, H3, H4, H5, H8, H10, H11, and H14.

Discussion

The research findings show that during the difficult times of the Covid 19 pandemic, which limits all social and economic activities, students are willing to switch from physical space learning to digital-based learning with a hybrid system. The results of the theoretical model have been presented previously in Figure 1. Motivation and intention to switch (MIS) and Decision Self Efficacy (DSE) which are mediating variables, where MIS represents new motivations and intentions in learning during the Covid pandemic, so that students are able to demonstrate behavior appropriate for switching to hybrid learning. This is in line with finding of previous study that found often students are psychologically more determined to participate in online learning (Reeve, 2012). Students also tend to follow certain online learning with more focus and will increase learning efforts, so they are able to follow the learning smoothly (Beqiri et al., 2009).

Another aspect that is considered as the second mediating variable that is able to increase the behavior of switching to hybrid learning is Decision Self Efficacy (DSE). DSE is important for students to be able to decide whether they should switch to hybrid learning or not, based on strong self-confidence. This result is in line with previous study that students (as technology adopters) examine and evaluate every choice they make. Students also evaluate how easily they can integrate various offerings in online learning with existing learning (Sajjad et al., 2020). It should be noted that although there is no influence between the push and pull variables on motivation and intention to switch (MIS). This is because indicators of perceived security risk, learning comfort, quality of service, behavior of lecturers and employees, available technology devices, and the usefulness and ease of use of various existing technologies have not been able to increase efficiency in learning. Students also do not intend to take hybrid-based courses/certifications, because they must focus on hybrid learning, and efforts are still needed to adjust to hybrid learning.

The results of this study contradict those of previous studies that state motivation and intention to switch include aspects such as students becoming more determined and devoting themselves to increasing efforts in online learning (Crawford et al., 2020; Hodges et al., 2020). The author found that students were not very interested in taking hybrid learning because they only gave introductory courses. Students often try to learn new knowledge, which makes them have to take the time to understand it, in line with previous research (Jha, S., & Bhattacharyya, 2013). In addition, there is no influence on the push and pull effect variables on Switching Behavior (SB) through Motivation and Intention to Switching (MIS) and Decision Self Efficacy (DSE), because students feel a mismatch in hybrid learning, which transitions quickly. Students also have to adapt in using the various features of the available hybrid learning platforms, so they take longer than offline learning. However, these shortcomings indicate that the switch to hybrid learning as a substitute for offline learning will be a consideration for students to complete all existing learning. They also believe that they are capable of substantially switching to a hybrid learning model.

In line with research by previous research, the authors found that DSE consists of individual student choices to participate in hybrid learning, which is based on easy-to-use technology, and is equipped with various interactive features, and makes the learning process more flexible (Zimmerman & Kulikowich, 2016). Finally, when students switch from offline learning to hybrid learning during the critical period of Covid 19, they are interested in improving their performance through hybrid learning, because hybrid learning is reliable (Y. H. Chen & Keng, 2019; Hodges et al., 2020). This is called switching behavior, which is the dependent variable in this study. Thus, the authors validate the research findings and convergent results with the existing literature. As proposed in the previous section, the validation of all hypotheses has been discussed. PushEff has a significant effect on SB with a coefficient of 0.259 and sig. <0.001. PullEff has a significant effect on SB with a coefficient of 0.232 and sig. 0.003. MoorEff has a significant effect on SB with a coefficient of 0.168 and sig. 0.025. The three results of the validation of the hypothesis are in line with the research that state there is an effect of variablePushEff, PullEff and MoorEff on switching behavior partially (Nayak et al., 2022).

PushEff has a significant effect on MIS with a coefficient of 0.062 and sig. 0.237. PullEff has a significant effect on MIS with a coefficient of 0.053 and sig. 0.271. The two rejections of the hypothesis are contrary to previous research (Dauda & Lee, 2015; Hsieh et al., 2012; Yu et al., 2017). And MoorEff has a significant effect on MIS with a coefficient of 0.704 and sig. <0.001, a hypothesis. PushEff has a significant effect on DSE with a coefficient of 0.129 and sig. 0.066. This is contrary to the research of other study which emphasizes the importance of knowledge and awareness of technology platforms for technology adoption (De Mattos & Laurindo, 2017). PullEff has a significant effect on DSE with a coefficient of 0.232 and sig. 0.003. These results validate the results of previous research regarding the attractiveness of alternative media in technology adoption scenarios (Chuah et al., 2017). Meanwhile, MoorEff has a significant effect on DSE with a coefficient of 0.554 and sig. <0.001.

PushEff has a significant effect on SB through MIS and DSE with a coefficient of 0.049 and sig. 0.286. PullEff has a significant effect on SB through MIS and DSE with a coefficient of 0.073 and sig. 0.201. The results of this study contradict with previous study who have confirmed in their study the effect of self-efficacy in decision making (Ray et al., 2019). MoorEff has a significant effect on SB through MIS and DSE with a coefficient of 0.328 and sig. <0.001. Other studies have supported a similar effect of the mooring effect on intention to adopt technology and behavioral switch to hybrid learning (Jung et al., 2012; Sawang et al., 2013). Thus, the empirical model establishes the relationship between the variables PushEff, PushEff, and MoorEff on SB directly, as well as through MIS and DSE as mediating variables, as well as the relationship between MIS and DSE on SB directly. This relationship is in line with the main principles of the PPM framework (Nayak et al., 2022; Wang & Lin, 2012). As the end of the discussion, that students are willing to switch to hybrid learning due to the circumstances and conditions of the learning environment affected by the Covid 19 pandemic. On the other hand, the limitation of this study is that data collection from respondents was only carried out at the Faculty of Economics, Universitas Negeri Semarang.'

The managerial implication of this research is that the research results obtained can be used as behavioral guidelines in switching to hybrid learning in the post-covid 19 period for students based on the push, pull and mooring effects involved. Support for the intention to switch to hybrid learning contributes greatly to the achievement of research objectives. It is strongly recommended that this switching behavior can be improved, as well as the importance of increasing support for the existing contextual environment. Both are priorities for fostering the behavior of switching to hybrid learning. Although the data processing was based on statistical rules and the PPM framework, deviations from the findings of this study were possible within the tolerance limits set during data analysis. The suggestion that the authors can give is for students to take part in a hybrid learning workshop that is able to motivate and improve the quality of learning. Meanwhile, universities are advised to increase socialization and training programs or certification of competence in mastering technology for students. Further research is suggested to improve this research by expanding the scope of the sample to be wider, namely students in the fields of social sciences and exact sciences, and modifying the model to be more complex with other relevant variables.

4. CONCLUSION

The conclusion of this study is that the push effect, pull effect, mooring effect, decision self-efficacy and motivation and intention to switch partially affect switching behavior. While the push and pull effect variables have no effect on motivation and intention to switch. Likewise, the effect of the mediating variable, namely the push and pull effect does not affect switching behavior through motivation and intention to switch and decision self-efficacy, in contrast to the mooring effect which has a significant effect. The findings of this study are hybrid learning has not been able to improve student performance compared to offline learning.

5. REFERENCES

Antee, A. (2021). Student perceptions and mobile technology adoption: implications for lower-income students shifting to digital. *Educational Technology Research and Development*, *69*(1), 191–194. https://doi.org/10.1007/s11423-020-09855-5.

Bansal, H. S., Taylor, S. F., & St. James, Y. (2005). '"Migrating"' to new service providers: Toward a unifying framework of consumers' switching behaviors. *Journal of the Academy of Marketing Science*, *33*(1), 96–115. https://doi.org/10.1177/0092070304267928.

Beqiri, M. S., Chase, N. M., & Bishka, A. (2009). Online course delivery: An empirical investigation of factors affecting student satisfaction. *Journal of Education for Business*, *82*(2), 95–100. https://doi.org/10.1080/08832320903258527.

Chen, N. S., Ko, H. C., Kinshuk, & Lin, T. (2005). A model for synchronous learning using the Internet. *Innovations in Education & Teaching International*, *42*(2), 181–194. https://doi.org/10.1080/14703290500062599.

Chen, Y. H., & Keng, C. J. (2019). Utilizing the push-pull-mooring-habit framework to explore users' intention to switch from oline to online real-person English learning platform. *Internet Research*, *29*(1), 167–193. https://doi.org/10.1108/IntR-09-2017-0343.

Cheng, S., Lee, S.-J., & Choi, B. (2019). An empirical investigation of users' voluntary switching intention for mobile personal cloud storage services based on the push-pull-mooring framework. *Computers in Human Behavior*, *98*, 198–215. https://doi.org/10.1016/j.chb.2018.10.035.

Chuah, S. H. W., Marimuthu, M., Kandampully, J., & Bilgihan, A. (2017). What drives gen y loyalty? Understanding the mediated moderating roles of switching costs and alternative attractiveness in the value-satisfaction-loyalty chain. *Journal of Retailing and Consumer Services*, *36*, 124–136. https://doi.org/10.1016/j.jretconser.2017.01.010.

Crawford, J., Percy, A., & Kelder, J. A. (2020). Connection, digital education, and student-centric teaching practice before COVID-19. *Journal of University Teaching & Learning Practice*, *17*(3), 1–5. https://doi.org/10.53761/1.17.3.1.

Cunningham, U. (2014). Teaching the disembodied: Othering and activity systems in a blended synchronous learning situation. , https://doi.org/10.19173/irrodl.v15i6.1793. *International Review of Research in Open and Distance Learning*, *15*(6), 33–51. https://doi.org/10.19173/irrodl.v15i6.1793.

Dauda, S. Y., & Lee, J. (2015). Technology adoption: A conjoint analysis of consumers′ preference on future online banking services. *Information Systems*, *53*, 1–15. https://doi.org/10.1016/j.is.2015.04.006.

De Mattos, C. A., & Laurindo, F. J. B. (2017). Information technology adoption and assimilation: Focus on the Suppliers Portal. *Computers in Industry*, *85*, 48–57. https://doi.org/10.1016/j.compind.2016.12.009.

Díaz, J. E. M. (2020). Virtual World as a Complement to Hybrid and Mobile Learning. *International Journal of Emerging Technologies in Learning (IJET)*, *15*(22), 267. https://doi.org/10.3991/ijet.v15i22.14393.

Ebner, C., & Gegenfurtner, A. (2019). Learning and satisfaction in webinar, online, and face-to-face instruction: a meta-analysis. *In Frontiersin Education*, *4*(92). https://doi.org/10.3389/feduc.2019.00092.

Farrell, O., & Brunton, J. (2020). A balancing act: a window into online student engagement experiences. *International Journal of Educational Technology in Higher Education*, *17*(1), 1–19. https://doi.org/10.1186/s41239-020-00199-x.

Firth, J., Siddiqi, N., Koyanagi, A., Siskind, D., Rosenbaum, S., Galletly, C., & Chatterton, M. L. (2019). The lancet psychiatry commission: A blueprint for protecting physical health in people with mental illness. *The Lancet Psychiatry*, *6*(8), 675–712. https://doi.org/10.1016/S2215-0366(19)30132-4.

Hodges, C., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). The diference between emergency remote teaching and online learning. *Educause Review*, *27*, 1–12. http://hdl.handle.net/10919/104648.

Hou, A. C., & Shiau, W. L. (2020). Understanding Facebook to Instagram migration: a push-pull migration model perspective. *Information Technology and People*, *33*(1), 272–295. https://doi.org/10.1108/ITP-06-2017-0198.

Hsieh, J. K., Hsieh, Y. C., Chiu, H. C., & Feng, Y. C. (2012). Post-adoption switching behavior for online service substitutes: A perspective of the push–pull–mooring framework. *Computers in Human Behavior*, *28*(5), 1912–1920. https://doi.org/10.1016/j.chb.2012.05.010.

Hsu, J. S. C. (2014). Understanding the role of satisfaction in the formation of perceived switching value. *Decision Support Systems*, *59*, 152–162. https://doi.org/10.1016/j.dss.2013.11.003.

Jha, S., & Bhattacharyya, S. S. (2013). Learning orientation and performance orientation: Scale development and its relationship with performance. *Global Business Review*, *14*(1), 43–54. https://doi.org/10.1177/0972150912466443.

Joshi, A., Vinay, M., & Bhaskar, P. (2021). Impact of coronavirus pandemic on the Indian education sector: perspectives of teachers on online teaching and assessments. *Interactive Technology and Smart Education*, *18*(2), 205–226. https://doi.org/10.1108/ITSE-06-2020-0087.

Jung, J., Chan-Olmsted, S., Park, B., & Kim, Y. (2012). Factors afecting e-book reader awareness, interest, and intention to use. *NewMedia & Society*, *14*(2), 204–224. https://doi.org/10.1177/1461444811410407.

Lin, C. L., Jin, Y. Q., Zhao, Q., Yu, S. W., & Su, Y. S. (2021). Factors inluence students' switching behavior to online learning under COVID-19 pandemic: A push–pull–mooring model perspective. *The Asia-Pacific Education Researcher*, *30*, 1–17. https://doi.org/10.1007/s40299-021-00570-0.

Martin, F., Parker, M. A., & Deale, D. F. (2012). Examining interactivity in synchronous virtual classrooms. *International Review of Research in Open and Distance Learning*, *13*(3), 227–261. https://doi.org/10.19173/irrodl.v13i3.1174.

Nayak, B., Bhattacharyya, S. S., Goswami, S., & Thakre, S. (2022). Adoption of online education channel during the COVID-19 pandemic and associated economic lockdown: an empirical study from push–pull-mooring framework. *Journal of Computers in Education*, *9*(1), 1–23. https://doi.org/10.1007/s40692-021-00193-w.

Oerther, D. B., & Peters, C. A. (2020). Educating heads, hands, and hearts in the COVID-19 classroom. *Environmental Engineering Science*, *37*(5), 303–303. https://doi.org/10.1089/ees.2020.0161.

Ray, A., Bala, P. K., & Dasgupta, S. A. (2019). Role of authenticity and perceived beneits of online courses on technology-based career choice in India: A modiied technology adoption model based on career theory. *International Journal of Information Management*, *47*, 140–151. https://doi.org/10.1016/j.ijinfomgt.2019.01.015.

Reeve, J. (2012). A self-determination theory perspective on student engagement. *In S. L. Christenson, A. L. Reschly, & C. Wylie*, 149–172. https://doi.org/10.1007/978-1-4614-2018-7_7.

Sajjad, A., Chu, J., Anwar, M. A., & Asmi, F. (2020). Between Green and Gray: Smog risk and rationale behind vehicle switching. *Journal of Cleaner Production*, *244*, 118674. https://doi.org/10.1016/j.jclepro.2019.118674.

Sawang, S., Newton, C., & Jamieson, K. (2013). Increasing learners' satisfaction/intention to adopt more e-learning. *Education + Training*, *55*(1), 83–105. https://doi.org/10.1108/00400911311295031.

Sindi, H., Nour, M., Rawa, M., Öztürk, Ş., & Polat, K. (2021). A novel hybrid deep learning approach including combination of 1D power signals and 2D signal images for power quality disturbance classification. *Expert Systems with Applications*, *174*, 114785. https://doi.org/https://doi.org/10.1016/j.eswa.2021.114785.

Stewart, A. R., Harlow, D. B., & DeBacco, K. (2011). Students' experience of synchronous learning in distributed environments. *Distance Education*, *32*(3), 357–381. https://doi.org/10.1080/01587919.2011.610289.

Su, Y. S., & Wu, S. Y. (2020). Applying data mining techniques to explore user behaviors and viewing video patterns in converged IT environments. *Journal of Ambient Intelligence and Humanized Computing*, 1–8. https://doi.org/10.1007/s12652-020-02712-6.

Susanty, A., Handoko, A., & Puspitasari, N. B. (2020). Push-pull mooring framework for e-commerce adoption in small and medium enterprises. *Journal of Enterprise Information Management*, *33*(2), 381–406. https://doi.org/10.1108/JEIM-08-2019-0227.

Tang, Z., & Chen, L. (2020). An empirical study of brand microblog users' unfollowing motivations: The perspective of push-pullmooring model. *International Journal of Information Management*, *52*, 102066. https://doi.org/10.1016/j.ijinfomgt.2020.102066.

Wang, K., & Lin, C. L. (2012). The adoption of mobile valueadded services. Managing Service Quality. *An International Journal*, *22*, 184–208. https://doi.org/10.1108/09604521211219007.

Xu, Y. C., Yang, Y., Cheng, Z., & Lim, J. (2014). Retaining and attracting users in social networking services: An empirical investigation of cyber migration. *The Journal of Strategic Information Systems*, *13*(3), 239–253. https://doi.org/10.1016/j.jsis.2014.03.002.

Yu, T. K., Lin, M. L., & Liao, Y. K. (2017). Understanding factors inluencing information communication technology adoption behavior: The moderators of information literacy and digital skills. *Computers in Human Behavior*, *71*, 196–208. https://doi.org/10.1016/j.chb.2017.02.005.

Zhang, K. Z., Cheung, C. M., & Lee, M. K. (2012). Online service switching behavior: The case of blog service providers. *Journal of Electronic Commerce Research*, *13*(3), 184. http://ojs.jecr.org/jecr/sites/default/files/13_3_p01.pdf.

Zimmerman, W. A., & Kulikowich, J. M. (2016). Online learning self-eicacy in students with and without online learning experience. *American Journal of Distance Education*, *30*(3), 180–191. https://doi.org/10.1080/08923647.2016.1193801.