J. Comput. Educ.
https://doi.org/10.1007/s40692-021-00206-8

Primary science curriculum student acceptance of blended learning: structural equation modeling and visual analytics

Xu Liu[1]

Received: 6 May 2021 / Revised: 24 August 2021 / Accepted: 11 October 2021

Abstract This paper focuses on the analysis of perceived usefulness (PU), perceived ease-of-use (PE), perceived playfulness (PP), community support (CS), and other factors that affect the acceptance of Chinese students (SA) in Blended learning of primary science curriculum. Based on technology acceptance model and Unified Theory of Acceptance and Use of Technology, an initial structural equation model is proposed. The initial structural model is for blended learning student acceptance (SA) in primary science curriculum. It contains five latent variables, and 4 latent variables can affect SA. Questionnaire responses are collected through blended learning SA questionnaire survey and analyzed using statistical methods. The questionnaire has 25 questions and collects 357 answers from all over China. Based on the reliability analysis, exploratory factor analysis, and confirmatory factor analysis of the data, the initial structural equation model is improved. According to the final structural equation model, the influence order of influencing factors on primary science curriculum blended learning SA is CS > PP > PU > PE. Based on the final model, an interactive visualization application is designed and implemented using SAP Analytics Cloud to allow users to understand the model easily and explore interactions among these factors visually. Teachers can directly see the changes of various factors through visualization, and do not need to pay attention to complex model details. This approach provides new practice for the application of theoretical models in Pedagogy.

Keywords Structural equation model · Blended learning · Student acceptance · Primary science curriculum · Visual analytics

✉ Xu Liu
liuxu@ieee.org

[1] SAP Labs China, No. 1001 Chenhui Road, Pudong, Shanghai 201203, China

Published online: 28 October 2021

Abbreviations

TAM	Technology acceptance model
UTAUT	Unified Theory of Acceptance and Use of Technology
PE	Performance expectancy
EE	Effort expectancy
SI	Social influence
FC	Facilitating conditions
PU	Perceived usefulness
PE	Perceived ease-of-use
PP	Perceived playfulness
CS	Community support
SA	Student acceptance
ML	Maximum likelihood
GLS	Generalized least squares
KMO	Kaiser–Meyer–Olkin
SAC	SAP Analytics Cloud
VR	Virtual reality

Introduction

Blended learning is a new information technology-assisted teaching model in the twenty-first century (Powell et al., 2015). Blended learning has different definitions in different scenarios, but various definitions generally include the combination of traditional face-to-face learning and online learning (Picciano et al., 2013). Practices prove that blended learning can effectively improve learning performance (Means et al., 2013), and the central link of blended learning lies in the design of learning activities that are efficient, practical, and widely accepted by teachers and students (Bliuc et al., 2012). Most of the existing researches on blended learning design in China are mainly oriented to the effects of blended learning and are oriented to the teacher community. These researches focus on how to make teachers' teaching behaviors meet the requirements of blended learning (Yongjun & Xin, 2020). Existing researches on how to improve Chinese students' acceptance of blended learning are mostly focused on specific disciplines or undergraduate students (Li et al., 2021; Zhang et al., 2020). This paper focuses on primary school science curriculum student acceptance (SA) of blended learning in all of China and tries to identify these influencing factors and the relationship between various factors.

The study of SA is the application of Theory of Reasoned Action (TRA) in pedagogy. The theoretical basis is to regard students as the main body of education and believe that students' acceptance of educational technology can directly determine the effect of educational technology application. Using structural equation model as a quantitative research method to analyze blended learning SA is still not widely used in current blended learning research in China, especially for blended learning research of primary school science curriculum. The research results of SA research can be applied in the course practice of improving the analysis and design of blended learning activities, thereby improving the final educational effectiveness

(Zacharis, 2015). Furthermore, research on blended learning is a significant component in educational technology research, and the conclusions can have important theoretical significance and popularization value. The research can help enrich the theory of blended learning related education, and then establish a systematic theoretical foundation.

The main innovations of this paper are using newly designed questions to verify and improve the model, getting the new model that describes SA factors, and using a newly designed visual analysis approach to display the model interactively. The significant challenge of this paper in the construction of theoretical models is how to identify the main factors that can affect SA in primary science curriculum as latent variables according to the existing theoretical framework and the educational model of blended learning, and how to determine the relationships of these factors and establish appropriate observed variables for each factor. After the model is built and verified, visual analytics can be used to allow teachers and researchers to explore the model intuitively to improve educational practices.

Building one visualization application to demonstrate and use the final theoretical model is also a part of the creative work in this paper, which makes current research be different from other statistics-oriented research works. Traditional pedagogy theoretical research generally focuses on obtaining theoretical models, but in real-world classes, teachers are usually not interested in the details of the model and should not need to master it—they just need one intuitive method to get the idea of the model. Visual analytics is widely used in many areas, especially business and government, and visualization is proven as one of the efficient methods to understand real-world data and models (Choo & Liu, 2018). Statistical software products generally focus on data processing and do not focus on building interactive visualization applications. Benefit from the advancement of data visual analytic software products, it has been convenient to build a dedicated, easy-to-upgrade, and easy-to-share visualization application (Walny et al., 2019), which can be used to let end-users—primary school teachers—explore and understand the key factors of the model, and then improve their teaching practice.

Initial model

Theoretical basis

Technology acceptance model (TAM) is the main theoretical source for constructing primary science curriculum SA model of blended learning. Based on TRA, TAM absorbs the core ideas of Expectancy Theory and Self-Efficacy Theory, which are mainly used to explain and predict users' acceptance of information technology. The factors included in TAM are Perceived Usefulness (PU), Perceived Ease-of-Use (PE), External Variables, Attitude Towards (towards the specific technology, for example, mobile learning), Behavioral Intention to Use, and Actual System Use (Legris et al., 2003). PU and PE are two important factors that affect Actual System Use. TAM is widely used in research related to the acceptance of information

technology (Al-Azawei et al., 2017), especially in the field of E-commerce, and has obtained many research results that are more in line with actual situations. Figure 1 shows TAM schematic diagram.

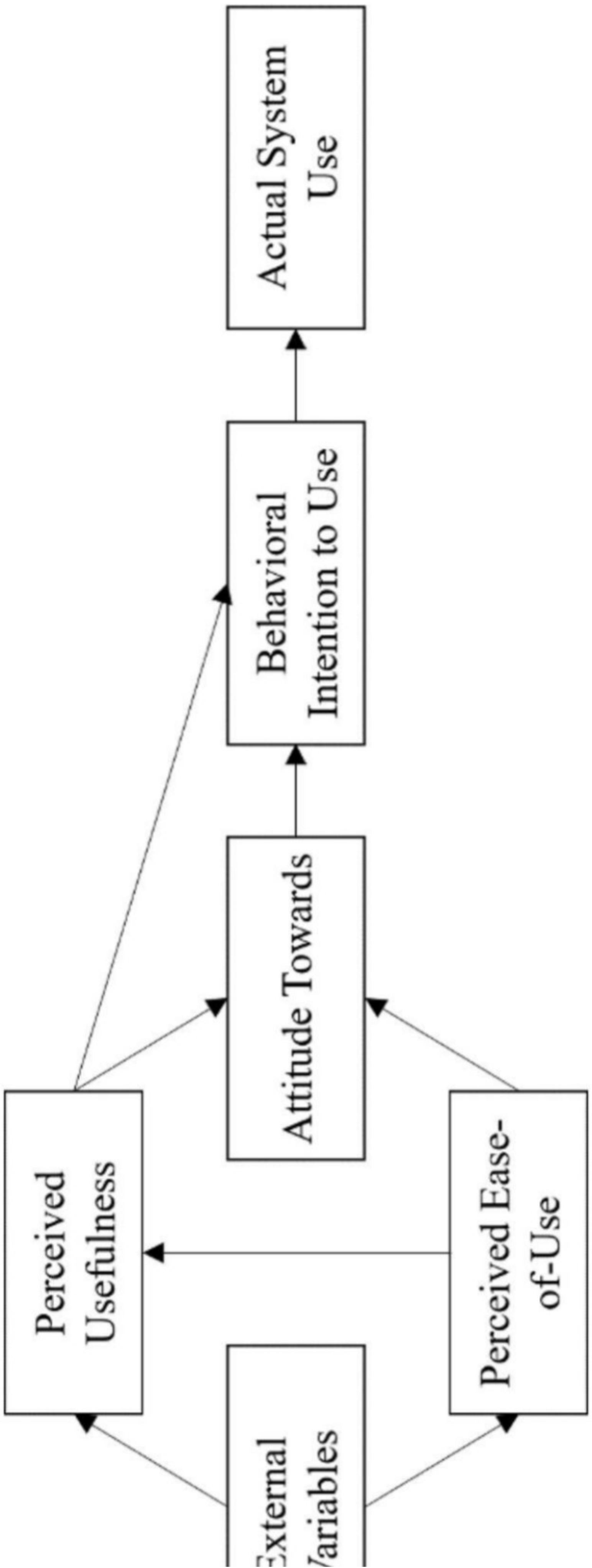
Unified Theory of Acceptance and Use of Technology (UTAUT) is also used for theoretical research on the acceptance of information technology. UTAUT can be treated as an extension based on the TAM. The focuses of the UTAUT model are also the factors that affect Behavioral Intention and Use Behavior. The model proposes four factors that affect the willingness and behavior including performance expectancy (PE), effort expectancy (EE), social influence (SI, an individual feels the importance that the others believe the individual should accept the new technology), and Facilitating Conditions (FC). Compared with TAM, PE in the UTAUT model is an expansion of the concept of PU in TAM, while EE is an expansion of the concept of PE in TAM. SI and FC are more refined than TAM's External Variables. Figure 2 shows UTAUT schematic diagram (Marchewka & Kostiwa, 2007).

Structural model

Structural equation model is mainly used for hypothesis testing and model evaluation (Xiong et al., 2015). TAM and UTAUT are used to describe the basic factors for information technology usages in social activities, and researchers usually need to improve the factors and relationships for special areas. The building of structural equation model for SA needs to focus on the interaction among multiple latent variables and the setting of the measurement variables corresponding to each latent variable and need to be verified and corrected based on survey data. Since structural equation model is a confirmatory analysis technique, the construction of the initial model is directly related to the conclusion of the study. To establish a suitable initial model, it is necessary to combine the corresponding theories of pedagogy, psychology, and management to explore the influencing factors, explore meanings and structural relationships of factors, and select appropriate observed variables to characterize each factor.

A structural model and a measurement model together constitute a structural equation model. As mentioned above, both TAM and UTAUT can be used to design the structural model. Compare to TAM, UTAUT is younger and becoming more and more popular be references in recent years, but there are also some doubts about the application of this theory. According to one literature-based research (Dwivedi et al., 2010), research results of using TAM and using UTAUT are highly overlapped. There is no significant evidence to show UTAUT has special advantages in research practices. Many articles that cited UTAUT do not actually use the theory, or just partial use of it (especially without considering the use of moderating factors)

(Williams et al., 2011). TAM is proposed earlier. TAM has been used more widely to study information system or information technology adoption, and it is verified by many studies across various business and management-related disciplines (Sani et al., 2020). So, TAM should be more solid and reliable. In this study, TAM is



gram

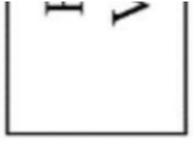


Fig. 1 TAM schematic dia

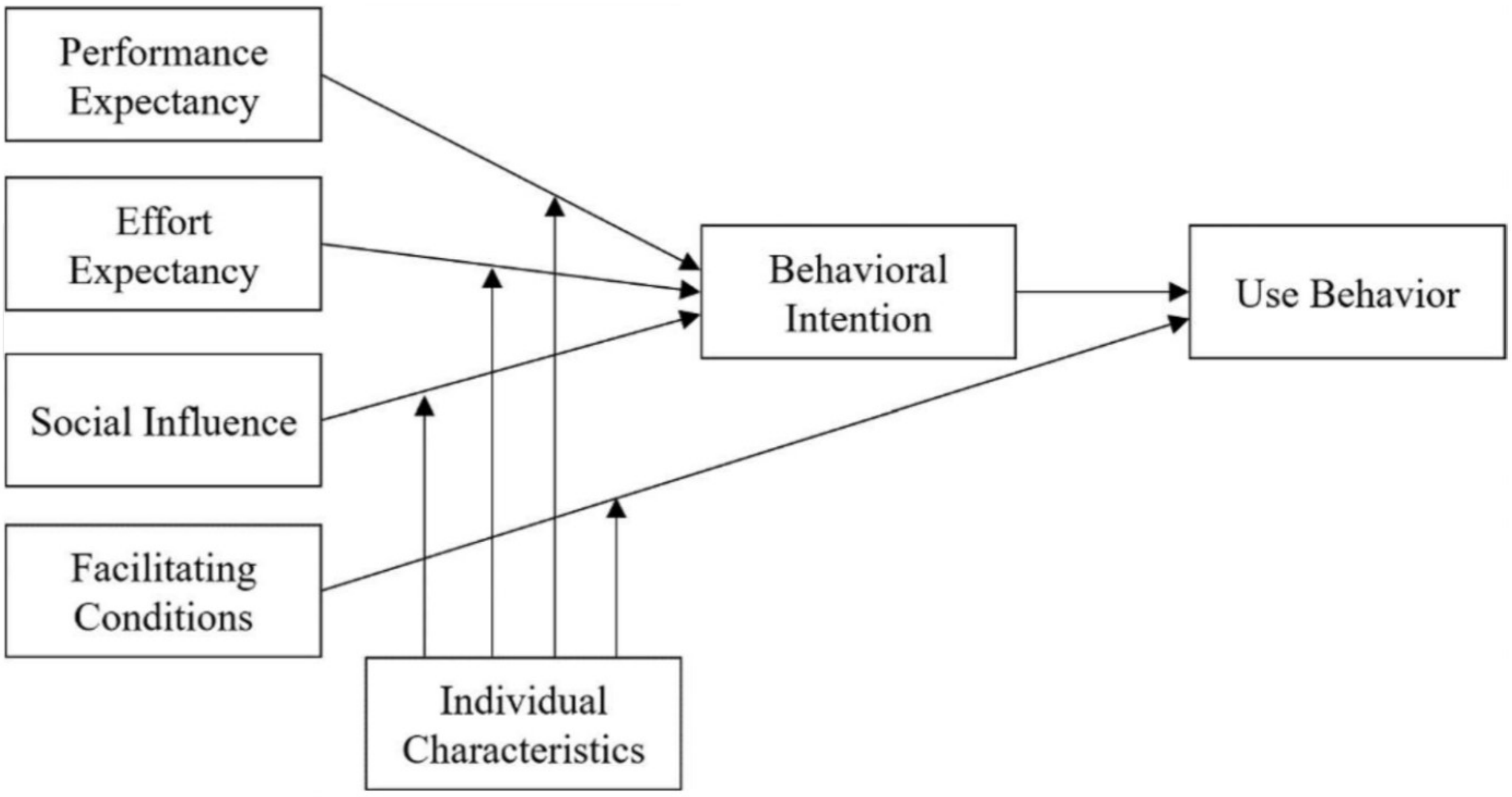


Fig. 2 UTAUT schematic diagram

selected as the base model, and the initial structural model also absorbs some of the characteristics of UTAUT.

In this paper, the initial structural model has 5 latent variables: PU, PE, perceived playfulness (PP), community support (CS), and SA. The construction of the structural model mainly refers to TAM. PE of blended learning affects PU, and other factors can affect the final acceptance through PU and PE. The construction process of the model also refers to the UTAUT model. The UTAUT model takes CS as an important factor influencing the willingness to use technology, emphasizing that individuals are influenced by surrounding groups. For primary school students, due to less knowledge accumulation and insufficient independence of life, existing relevant studies have proved that the degree of support from families, schools, and extracurricular communities will more easily affect their judgment and acceptance of things (Alam, 2015). Therefore, the model incorporates CS as a latent variable, and believes that CS for blended learning has an impact on SA, PU, and PP. As an influencing factor of acceptance, PP has been confirmed by many educational theoretical research literatures (Alshurideh et al., 2019; Estriegana et al., 2019; Padilla-Meléndez et al., 2013). Playfulness is one of the driving forces for humans to explore unknown fields (Bateson et al., 2013). The initial model believes that PE, PU, and SA are directly affected by PP of students in primary school curriculum

PU, and SA are directly affected by PP of students in primary school curriculum. Figure 3 is the initial structural model (M1) diagram constructed in this paper.

Student performance, which is the result of SA, can be used to track the effectiveness of SA and infer the factors that change SA, yet student performance itself is not the key point of this research. Perceived fiscal cost, which is more frequently mentioned in other papers of acceptance research, is not included in M1. Perceived financial cost mainly comes from the theory of educational economics, but students usually have no source of revenue. The results of research on college students show that perceived financial cost does not have much effect on the acceptance of educational technology (Rabu & Talib, 2017). For primary school students, since it is

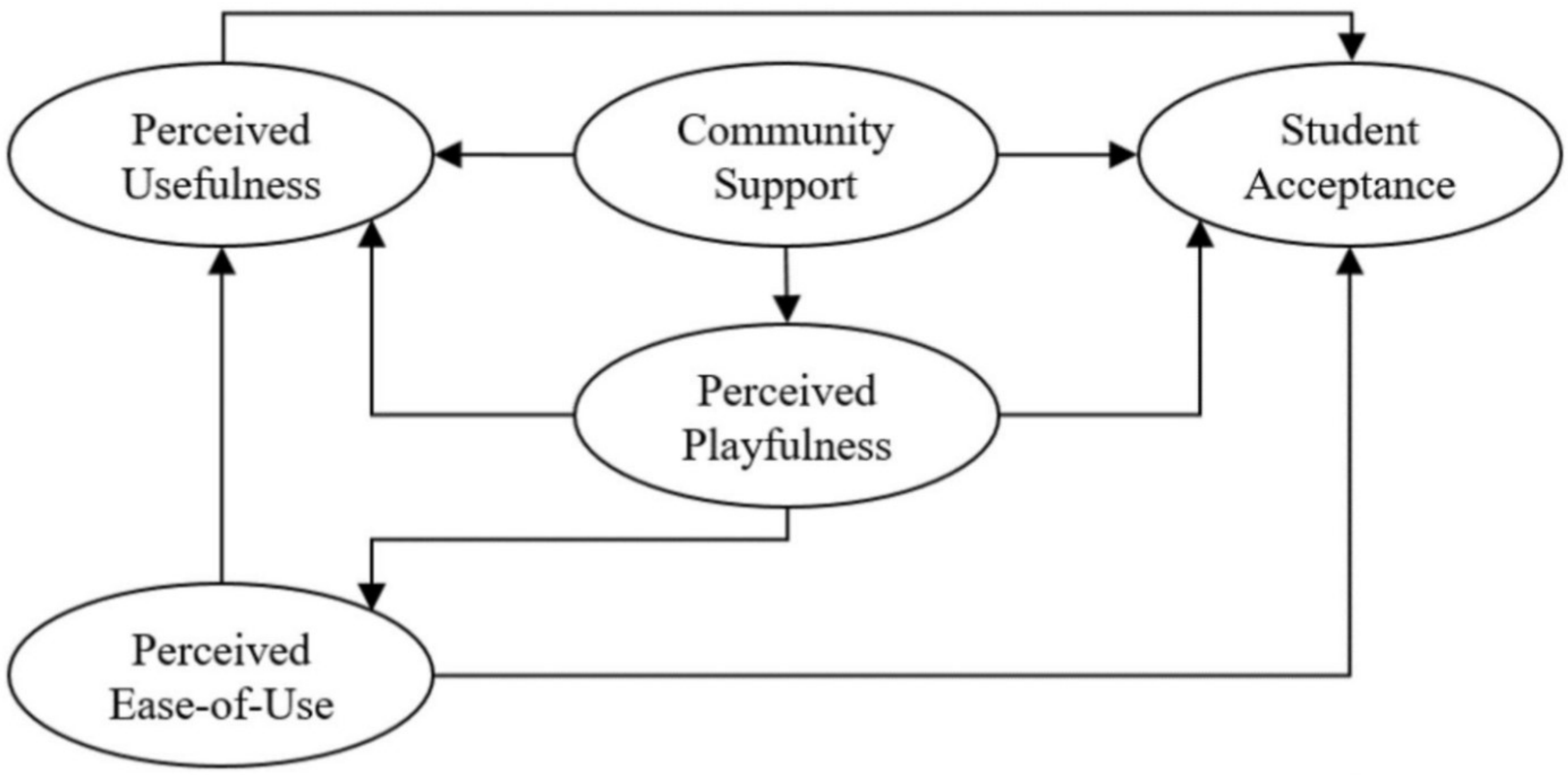


Fig. 3 Initial structural model M1

unlikely to achieve financial independence, it is even less likely to choose to accept or reject the blended learning model because of financial reasons.

Measurement model

Latent variables in the initial structural model cannot be directly observed, so corresponding observed variables need to be designed. The measurement of the observed variable itself depends on the questionnaire. Observed variables need to be designed to be easily measured and easy for respondents to understand. For a specific latent variable, which observed variables should be used and the specific problems that each observed variable depends on can be defined according to the relevant research literature and interviews. This paper mainly summarizes observed variables through literatures, with a few additional changes by this study researchers. Table 1 lists the questions used to measure all the observed variables (each latent variable has 5 observed variables).

Combined with the initial structural model and measurement model that have been designed, the structural equation model M1 that describes SA can be defined as Fig. 4 displays. Some "e" marks with numbers in the circle represent the residual of the internal dependent variables and the observed variables. Residual is not key point of this research.

Data collection and process

Questionnaire design

The designed primary school science curriculum blended learning SA questionnaire includes various observed variables in M1, which is composed of 25

Table 1 All questions on the questionnaire

Variables	Questions
PU_1	Blended learning meets my science learning needs (Venkatesh et al., 2003)
PU_2	Blended learning reduces the learning efficiency of my science curriculum
PU_3	Blended learning can solve the problems encountered in the classroom learning of science curriculum
PU_4	Blended learning can help me use spare time when studying science curriculum (Lin & Anol, 2008)
PU_5	Blended learning improves my learning effect on science curriculum (Wang et al., 2009)
PE_1	The Blended learning platform for science curriculum I am exposed to is difficult to learn quickly
PE_2	I think the blended learning platform of science curriculum is easy to use
PE_3	The operation of the blended learning platform for science curriculum is simple
PE_4	I think the various functions of blended learning platform of science curriculum are easy to master
PE_5	I can quickly adapt to blended learning methods in the study of science curriculum
CS_1	If my classmates like to study science curriculum through blended learning, I would like to participate
CS_2	If teachers support me to use blended learning methods in the science curriculum, I will be happy to use
CS_3	If my parents support me to use blended learning methods to study science curriculum, I will be happy to use
CS_4	If extracurricular activities and training institutions support me to use blended learning to study science curriculum, I will be happy to use
CS_5	Few people in my circle of friends know blended learning methods of science curriculum
PP_1	Using blended learning methods to study science curriculum can stimulate my curiosity (Huang et al., 2007)
PP_2	Learning science curriculum using blended learning methods makes my study more enjoyable (Liu et al., 2010)
PP_3	I feel that learning science curriculum through blended learning will distract me from studying
PP_4	In the learning process of science curriculum, blended learning methods are more interesting
PP_5	In the study of science curriculum, blended learning can guide me to explore knowledge more

SA_1	I am willing to learn new science curriculum using blended learning methods (Davis, 1989)
SA_2	I am willing to discuss with my classmates on blended learning platforms
SA_3	I am willing to take a quiz or record my learning results on blended learning platforms
SA_4	I am willing to use blended learning to make up for my lack of learning
SA_5	I am willing to recommend my friends to study science curriculum using blended learning (Donaldson, 2011)

questions. Regarding the choice of scale series, the finer granularity of the data is more accurate and more suitable for the actual situation, which is convenient for estimation using chi-square test and maximum likelihood method. However, if the scale is too fine, the respondent will face more options when answering, increasing the burden of the respondent, and it is more likely that the respondent will fill in incorrectly randomly. It will take more low quality and invalid

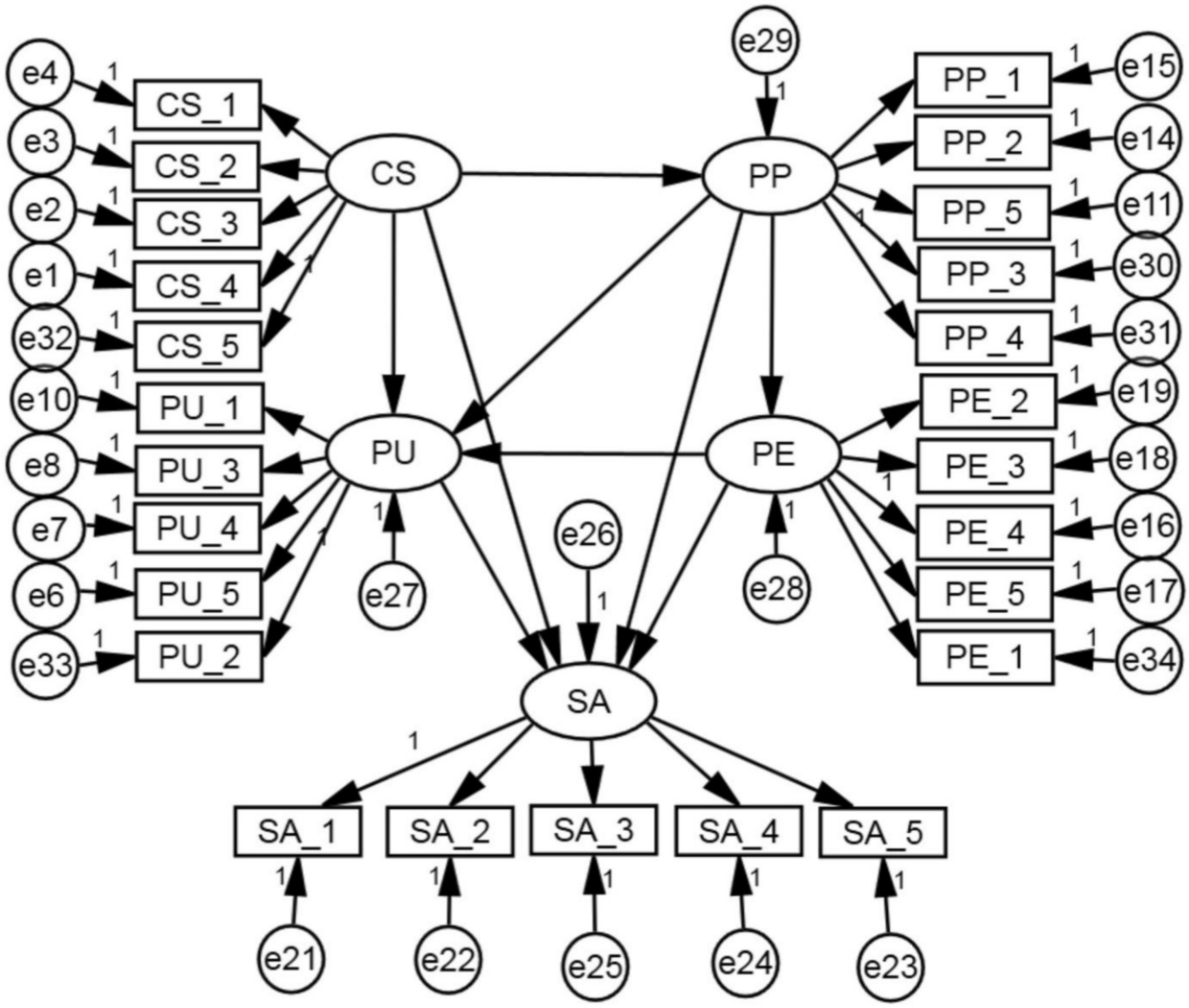


Fig. 4 Initial structural equation model M1

questionnaire results. It is generally considered that the 7-level scale is the most suitable, and mobile applications can be used to post the questionnaire (Liu et al., 2019). The online questionnaire platform selected in this study is Tencent, which

2019). The online questionnaire platform selected in this study is Tencent, which is because Tencent's interface design is user-friendly, and it has better support for instant messaging software such as WeChat and QQ (these two instant message applications are popular in China). All questions are translated into Chinese, and some instructions are added to allow parents and teachers help students to understand these questions. The 25 questions are divided into 5 pages, with 5 questions per page, so that the length of each screen is reduced, which is more suitable for mobile device users. Figure 5 displays screenshots of the questionnaire on mobile phones: (a) is the first page of the questionnaire and (b) is the third page of the questionnaire.

Online questionnaire surveys can breakthrough time and space constraints and reduce the burden of respondents filling out. For example, by recording the IP address of the respondent, user's location can be inferred. By recording the start time and end time of the respondent's answer to the question, we can get the time of submission of the questionnaire and calculate the duration of the respondent's answer. This eliminates the need for respondents to fill in

Fig. 5 The questionnaire on mobile phones

information such as region and date. The questionnaire filling procedure can also give prompts when filling in the questionnaire, avoiding inconsistencies due to inadequate answers, and reducing or even eliminating the occurrence of missing values. It is because software platforms can block many invalid inputs to force users to input valid values. However, due to the lack of face-to-face communication with the respondents, it is difficult to ensure the consistency between the respondents and the target group in social network questionnaire surveys. The response rate of social network questionnaires is usually lower than that of conventional methods (Grossmann et al., 2018). It means online questionnaire survey usually needs a lot of participators to get enough data.

In this research, QQ and WeChat are used to disseminate the questionnaire in all of China. Data collection lasts for about one week. A total of 357 completed and submitted questionnaires are collected in this study (these answers are from different provinces of China). The response rate of the questionnaire used in this study is 43% (the response rate of the online questionnaire refers to the ratio of the number of people who actually filled out and submitted the questionnaire to the number of people who viewed the questionnaire), and the

average completion time of the questionnaire is about 2 min. The original data of the study can be downloaded from IEEE DataPort (Blinded for Reviewing).

Initial data processing

The initial processing of the data is mainly to enter the data into the analysis software, process missing values and abnormal values of questionnaire answers, and delete the invalid questionnaire answers. Due to the approach of online questionnaire survey, two-dimensional table data can be directly exported in the background of the survey platform. Each row in the table records a questionnaire response. Since the online questionnaire requires respondents to select each option, there is no need to process missing values.

There are no restrictions on the sample area when the questionnaire is started, but obviously the respondents need to have a certain understanding of blended learning in primary science curriculum, which should exclude some students. For example, in this study, primary school teachers in some small cities directly refuse to distribute this questionnaire because the students had hardly been exposed to such learning methods. Figure 6 shows geographical distribution of respondents (this picture is generated automatically by Tencent questionnaire platform). It is easy to see that although the survey samples are distributed in many provinces of China, the main sources are Henan (河南), Shandong (山东), Shanghai (上海), Jiangsu (江苏), Guangdong (广东), and other populous provinces and economically developed regions. The top 5 provinces with the largest number of blended learning SA surveys have accounted for more than 50% of the total number of people surveyed (most of the answers are from respondents in the top 5 provinces). This shows from one aspect that education, as the superstructure of society, needs to be supported by a developed economy and a sufficient population. This is especially true for the application of blended learning in science and technology education. Through the geographical distribution map, economic development has an irreplaceable effect on the development of basic education. Geographical distribution also shows that the samples and conclusions of this study are not only geographically universal but also inevitably inclined.

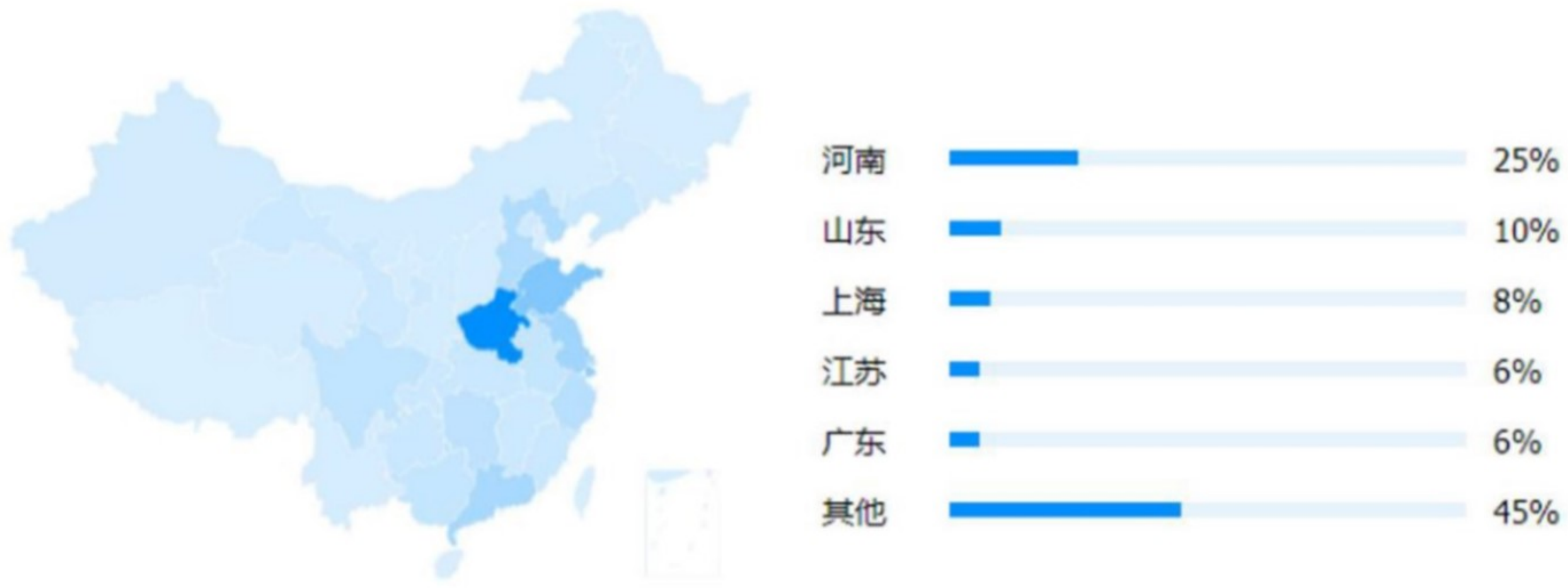


Fig. 6 Geographical distribution of respondents

For abnormal values handling, because the questionnaire contains reverse questions, the probability of answering the same value for all questions is extremely low. It is possible to exclude abnormal values by checking whether all options are filled with the same value (for example, all values are 7). Questionnaire answers with too short filling time are considered invalid data. In this study, 4 questionnaire answers with the shortest answer time are selected and deleted ("One questionnaire answer" means answering 25 questions. Each of these 4 answers uses no more than 1 min to answer all 25 questions. Two of the 4 answers have very short answer time (less than 10 s for 25 questions). They are probably answered by computer programs. In the effective data obtained, answers to reverse questions need to be adjusted to the positive direction.

Figure 7 shows 2 pie charts for the gender and grade distributions of the respondents. It can be seen from the figure that the survey subjects are evenly distributed in terms of gender, with slightly more males than females. In terms of grades, there are more respondents in the middle grades than in the junior grades, while the respondents in the senior grades obviously account for the majority. This shows that the survey and conclusions of this study are more inclined to target the senior grade students. With the accumulation of students' knowledge and the increase in the complexity of the curriculum, the higher the grade, the higher the level of awareness and participation of the students in the blended learning of science curriculum.

The descriptive statistical results (Table 2) show that the absolute value of skewness and absolute value of kurtosis are not greater than 1, which indicates that the data tend to be symmetrically distributed on both sides of the mean. From the mean value of the observed variables of the latent variables, the respondents have relatively high acceptance of blended learning—most means are above 5 points. The largest standard deviation is PU_2 (in the italic values), which indicates the difference in the evaluation of whether the respondents can improve learning efficiency in blended learning is the largest, and the smallest standard deviation is the italicized PP_4, indicating that the evaluations are the most consistent in terms of whether blended learning can improve the interest of learning.

When using structural equation model for analysis, the effective sample size should not be less than 200, preferably 10 to 15 times the observed variable number (Thompson, 2000). After processing these preliminary data, the remaining sample

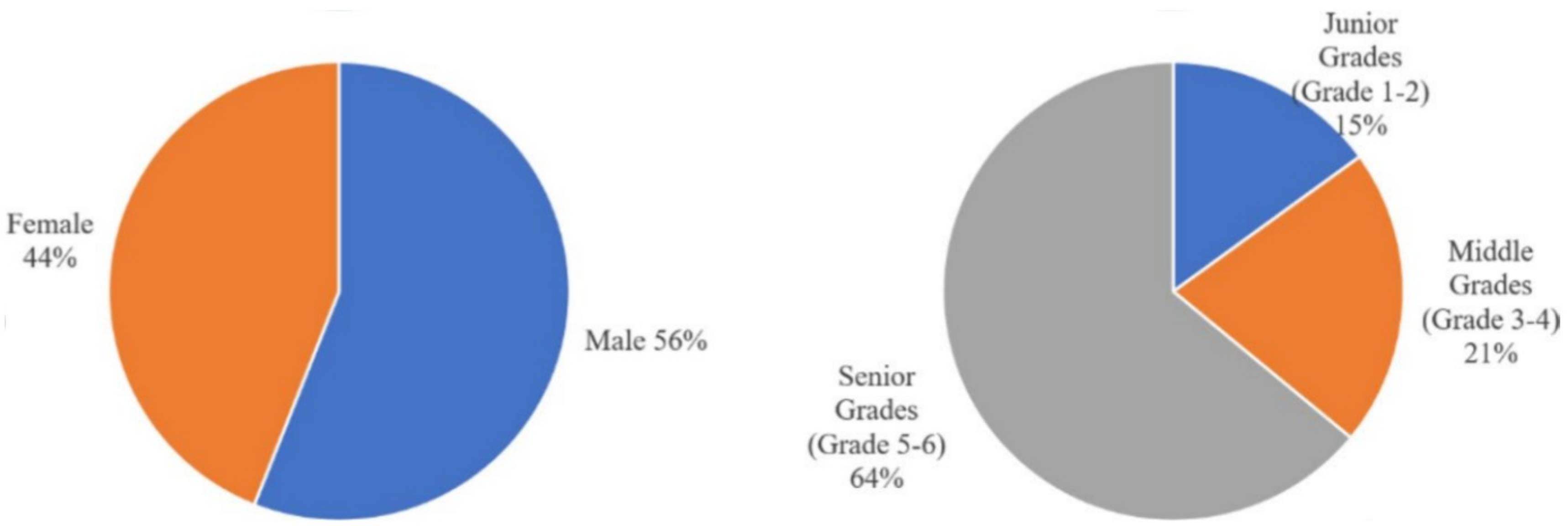


Fig. 7 Respondents' gender and grade distribution

Table 2 Descriptive statistics

Latent variables	Observed variables	Mean	SD	Skewness	Kurtosis
Perceived usefulness	PU_1	5.14	1.816	− 0.741	− 0.330
	PU_2	4.71	*1.962*	− 0.462	− 0.955
	PU_3	5.34	1.573	− 0.802	0.136
	PU_4	5.48	1.567	− 0.909	0.236
	PU_5	5.38	1.563	− 0.789	0.047
Perceived ease-of-use	PE_1	3.73	1.850	0.206	− 0.859
	PE_2	5.02	1.539	− 0.472	− 0.241
	PE_3	5.02	1.513	− 0.400	− 0.356
	PE_4	4.97	1.440	− 0.388	− 0.176
	PE_5	5.13	1.448	− 0.408	− 0.359
Community support	CS_1	5.51	1.544	− 0.985	0.437
	CS_2	5.52	1.455	− 0.811	0.272
	CS_3	5.55	1.469	− 0.904	0.360
	CS_4	5.40	1.539	− 0.760	− 0.074
	CS_5	3.12	1.778	0.474	− 0.602
Perceived playfulness	PP_1	5.57	1.490	− 1.017	0.588
	PP_2	5.47	1.480	− 0.853	0.342

	PP_3	4.10	1.912	– 0.004	– 1.078
	PP_4	5.54	*1.429*	– 0.872	0.226
	PP_5	5.63	1.430	– 0.964	0.468
Student acceptance	SA_1	5.55	1.512	– 1.059	0.729
	SA_2	5.45	1.503	– 0.916	0.395
	SA_3	5.48	1.546	– 0.960	0.486
	SA_4	5.59	1.489	– 1.138	1.085
	SA_5	5.55	1.462	– 0.959	0.567

size is 331, which is very suitable for 25 observed variables. Since the data obtained from the survey does not strictly obey the multivariate normal distribution, the default maximum likelihood (ML) method of AMOS software is not used to verify the structural equation model but generalized least squares (GLS) method is used (Shimizu & Kano, 2008; Xinni et al., 2015).

Reliability analysis

This study uses Cronbach's alpha method to check the internal consistency of the results of the questionnaire survey on primary science curriculum SA of blended learning (Chen & Yao, 2016). The Cronbach's alpha coefficients in the four subscales of the acceptance survey results of PU, PE, CS, and PP are generally not high, but if one question is deleted from each subscale, Cronbach's alpha coefficients in new subscales can be significantly improved. According to Table 3, these questions

Table 3 Reliability analysis of each subscale

Latent variable	Cronbach's alpha	Observed variable	Cronbach's alpha (if deleted)
Perceived usefulness	0.760	PU_1	0.708
		PU_2	*0.844*
		PU_3	0.674
		PU_4	0.684
		PU_5	0.649
Perceived ease-of-use	0.623	*PE_1*	*0.872*
		PE_2	0.435
		PE_3	0.427
		PE_4	0.439
		PE_5	0.456
Community support	0.696	CS_1	0.547
		CS_2	0.496
		CS_3	0.501
		CS_4	0.503
		CS_5	*0.935*

		CS_5	*0.935*
Perceived playfulness	0.782	PP_1	0.683
		PP_2	0.672
		PP_3	*0.932*
		PP_4	0.670
		PP_5	0.679
Student acceptance	0.952	SA_1	0.948
		SA_2	0.939
		SA_3	0.937
		SA_4	0.941
		SA_5	0.939

that should be deleted are PU_2, PE_1, CS_5, PP_3 (italic values). After deleting the 4 questions, Cronbach's alpha coefficients of the four subscales of PU, PE, CS, and PP meet the reliability requirements. The questionnaire question total number is changed to 21. It is not difficult to see that the deleted four questions are all in the form of reverse questions. It means that the use of reverse questions for primary school students is not a good practice. Reverse questions are misunderstandable, and the survey result quality will be affected.

Validity analysis based on exploratory factor analysis

Conducting KMO (Kaiser–Meyer–Olkin) test and Bartlett's Test of Sphericity on the survey data of survey data shows that the results of SA questionnaire survey are suitable for factor analysis (KMO value is 0.956, and the significance of Bartlett's

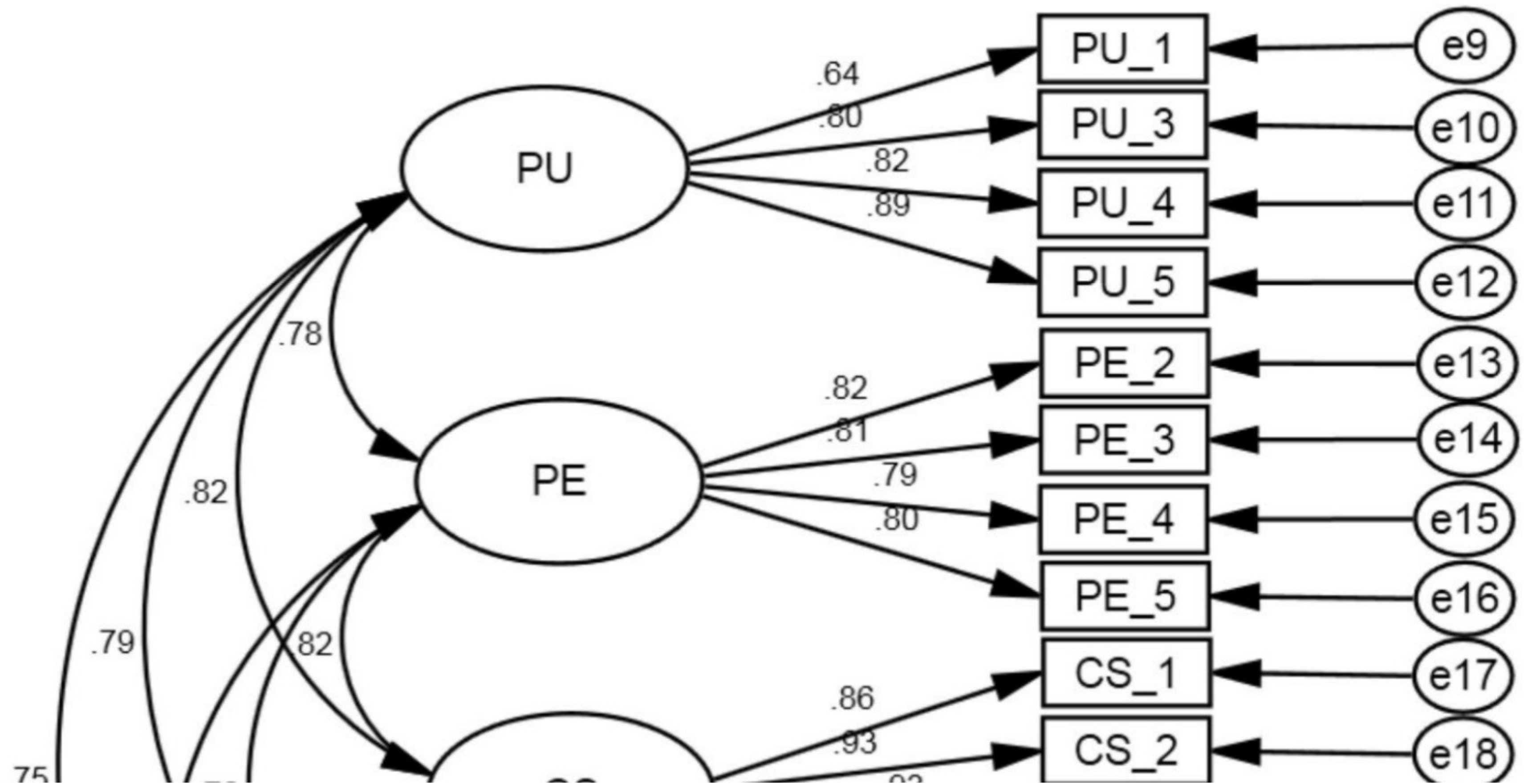
Test of Sphericity is 0.000). The specific method of exploratory factor analysis is to carry out principal component analysis. At the same time, the maximum variance method is used as the rotation method of factor extraction. The number of factors is fixed at 5. Based on the above research, the scree plot and total variance explanation table of the acceptance survey of blended learning are obtained. According to Table 4, the PP_4 observed variable measures two latent variables. According to the design requirements of the structural equation model, an observed variable should only be used to measure one latent variable, which shows that PP_4 is not a well-designed variable and should be deleted. The total number of questionnaire questions is changed to 20.

Validity analysis based on confirmatory factor analysis

For structural equation model, confirmatory factor analysis is usually used to verify the accuracy of the measurement model. A popular approach is constructing one special structural equation model to verify its measurement model. In this special structural equation model, every two latent variables in the model are marked as related. The measurement model contains those corresponding questions in the SA

Table 4 Rotated component matrix

Observed variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
SA_5	*0.844*	0.160	0.174	0.236	0.214
SA_4	*0.810*	0.149	0.237	0.236	0.243
SA_3	*0.791*	0.214	0.260	0.273	0.227
SA_2	*0.764*	0.209	0.361	0.238	0.214
SA_1	*0.710*	0.244	0.226	0.324	0.243
PE_3	0.173	*0.829*	0.227	0.106	0.121
PE_4	0.151	*0.794*	0.176	0.181	0.223
PE_2	0.150	*0.741*	0.124	0.222	0.338
PE_5	0.341	*0.593*	0.376	0.156	0.213
CS_3	0.343	0.275	*0.712*	0.342	0.248
CS_2	0.380	0.233	*0.704*	0.313	0.271
CS_1	0.238	0.348	*0.691*	0.231	0.278
CS_4	0.422	0.271	*0.664*	0.279	0.230
PP_2	0.395	0.221	0.278	*0.717*	0.243
PP_5	0.396	0.209	0.288	*0.700*	0.233
PP_1	0.316	0.286	0.317	*0.671*	0.297
PP_4	*0.507*	0.181	0.294	*0.634*	0.222
PU_5	0.298	0.164	0.332	0.260	*0.716*
PU_3	0.183	0.309	0.085	0.360	*0.697*
PU_4	0.283	0.184	0.369	0.132	*0.691*
PU_1	0.221	0.300	0.136	0.105	*0.636*



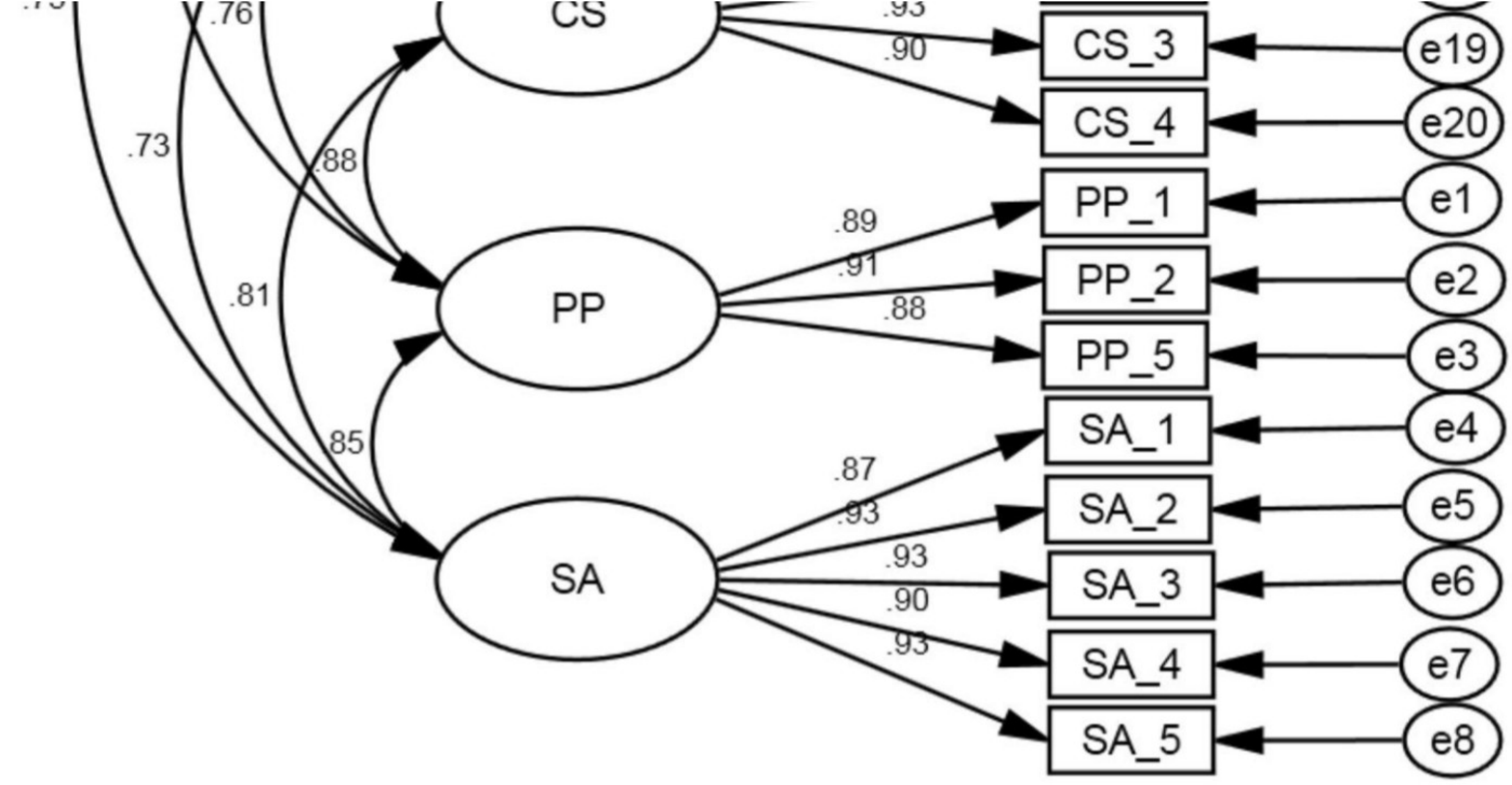


Fig. 8 Confirmatory factor analysis

questionnaire. It is not difficult to see that the structural model used by this special structural equation model has no theoretical value, and its focus is verifying the measurement model.

Figure 8 shows the special structural equation model for confirmatory factor analysis. All observed variables show a strong positive correlation with corresponding latent variables (standard regression coefficient values are between 0.64 and 0.93). According to the verification results (CMIN/DF is 2.164, GFI is 0.895, AGFI is 0.862, RMSEA is 0.059), it can be confirmed that the adaptability of the confirmatory factor analysis model is good, indicating that the corresponding measurement model is acceptable.

Final model

Model fitting and correction

Through data analysis, the structural equation model M1 has been updated to the improved structural equation model M2. Loading the improved structural equation model M2 and the sample data after data analysis can confirm that the structural equation model M2 is compatible with the questionnaire data. Figure 9 displays M2 (CMIN/DF is 2.274, GFI is 0.889, AGFI is 0.855, RMSEA is 0.062).

From the fitting results in Table 5, it can be found that three paths in M2 are insignificant: PP affects PU, PE affects SA, and CS affects SA (italic values. $P > 0.05$ means insignificant, and *** means $P < 0.001$. "Fixed" means if other factors for the latent variable in this measure model are significant, this factor is also significant). In M2, the path coefficient significance test value of PU to SA also does not meet the significance requirement, but the direct impact of PU on SA has been proved by many studies (Pitafi et al., 2020; Zhai & Shi, 2020), and the significance test value gap to significance requirement is rather smaller. Subsequent tests can prove that PU to SA significance test value can be improved to accepted levels after M2 is simplified. Deleting the three insignificant paths

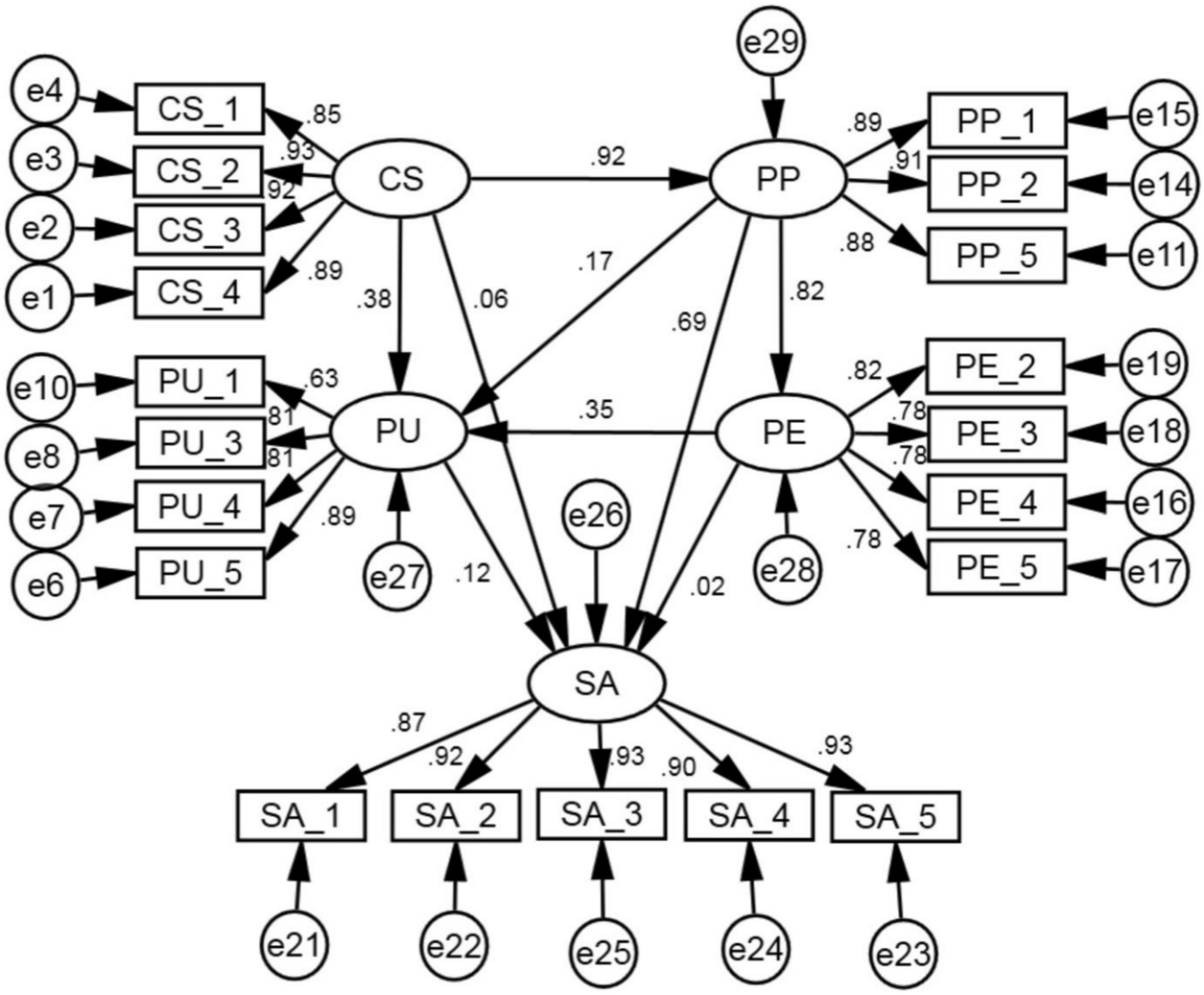


Fig. 9 Fitting result of structural equation model M2

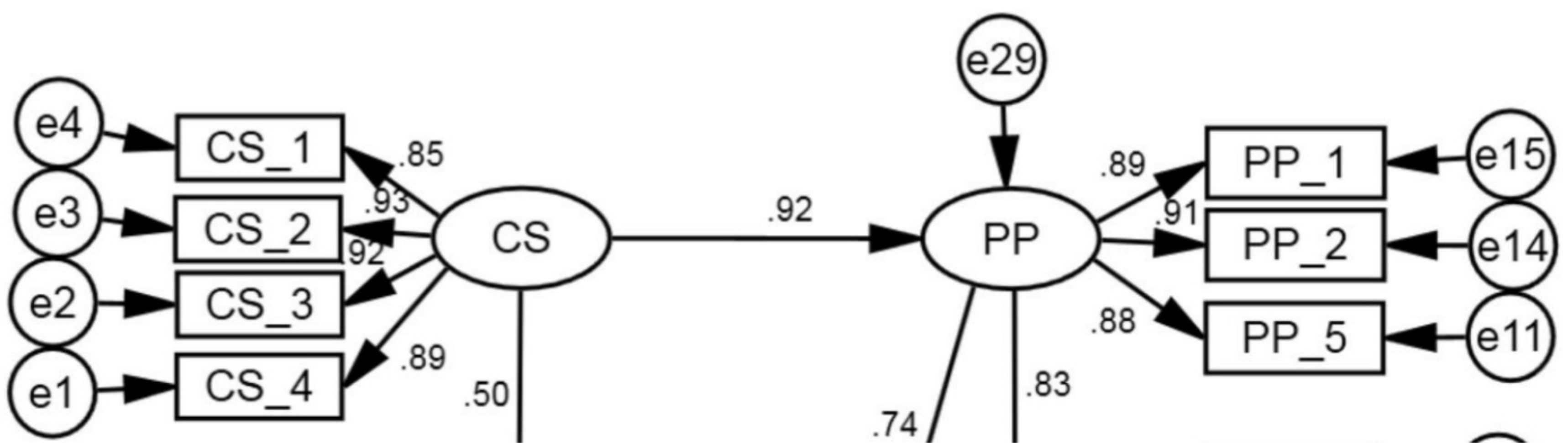
Table 5 M2 parameters

Model	Path	Standardized estimation	P
Structural model	PP ← CS	0.920	***
	PE ← PP	0.823	***
	PU ← CS	0.379	0.023
	PU ← PE	0.354	0.001
	PU ← PP	*0.168*	*0.431*
	SA ← PE	*0.016*	*0.877*
	SA ← PU	0.125	0.139
	SA ← CS	*0.065*	*0.675*

	SA←CS	0.065	0.675
	SA←PP	0.685	***
Measurement model	CS_2←CS	0.930	***
	CS_3←CS	0.923	***
	CS_4←CS	0.893	***
	PU_5←PU	0.889	Fixed
	PU_4←PU	0.813	***
	SA_1←SA	0.871	Fixed
	PE_4←PE	0.777	***
	PE_3←PE	0.776	***
	SA_2←SA	0.923	***
	SA_3←SA	0.926	***
	PE_5←PE	0.783	Fixed
	SA_4←SA	0.901	***
	SA_5←SA	0.933	***
	PP_2←PP	0.912	***
	PP_1←PP	0.886	***
	PU_3←PU	0.810	***
	PP_5←PP	0.881	Fixed
	CS_1←CS	0.846	Fixed
	PU_1←PU	0.627	***
	PE_2←PE	0.817	***

in the structural equation model M2 can obtain the modified model M3. Paths of M3 are more concise than M2, and M3 can reflect the essential relationship between the factors. Figure 10 shows M3 which has acceptable verification results (Bentler, 1992) (CMIN/DF is 2.237, GFI is 0.889, AGFI is 0.858, RMSEA is 0.061).

The fitting degree of M3 (which has fewer paths) is nearly the same as M2, which means M3 is an effective modification of M2. In this study, M3 is determined as the final structural equation model for primary science curriculum SA of blended learning. If we ignore measurement model, the final acceptance model based on M3 is shown in Fig. 11.



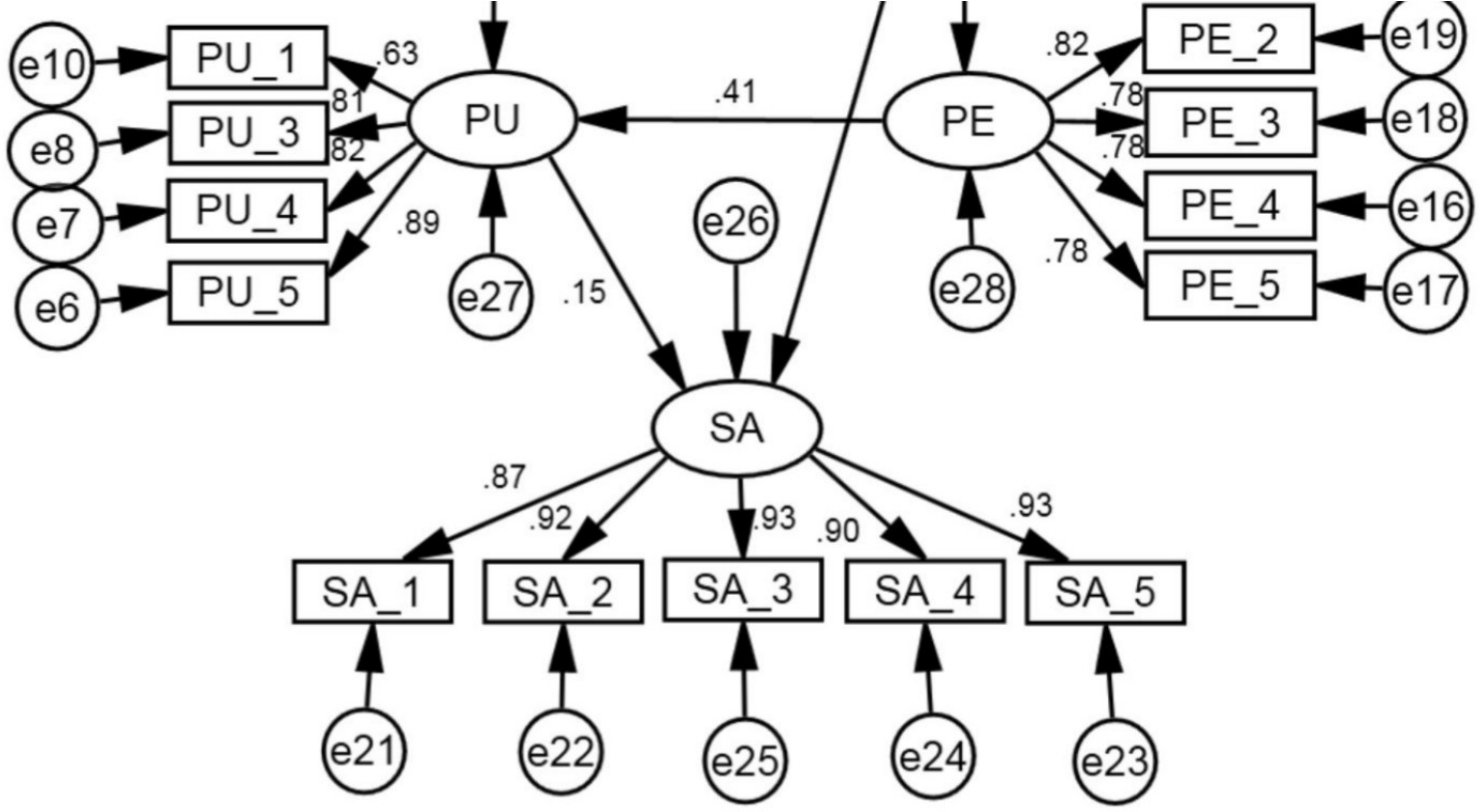


Fig. 10 Final structural equation model M3

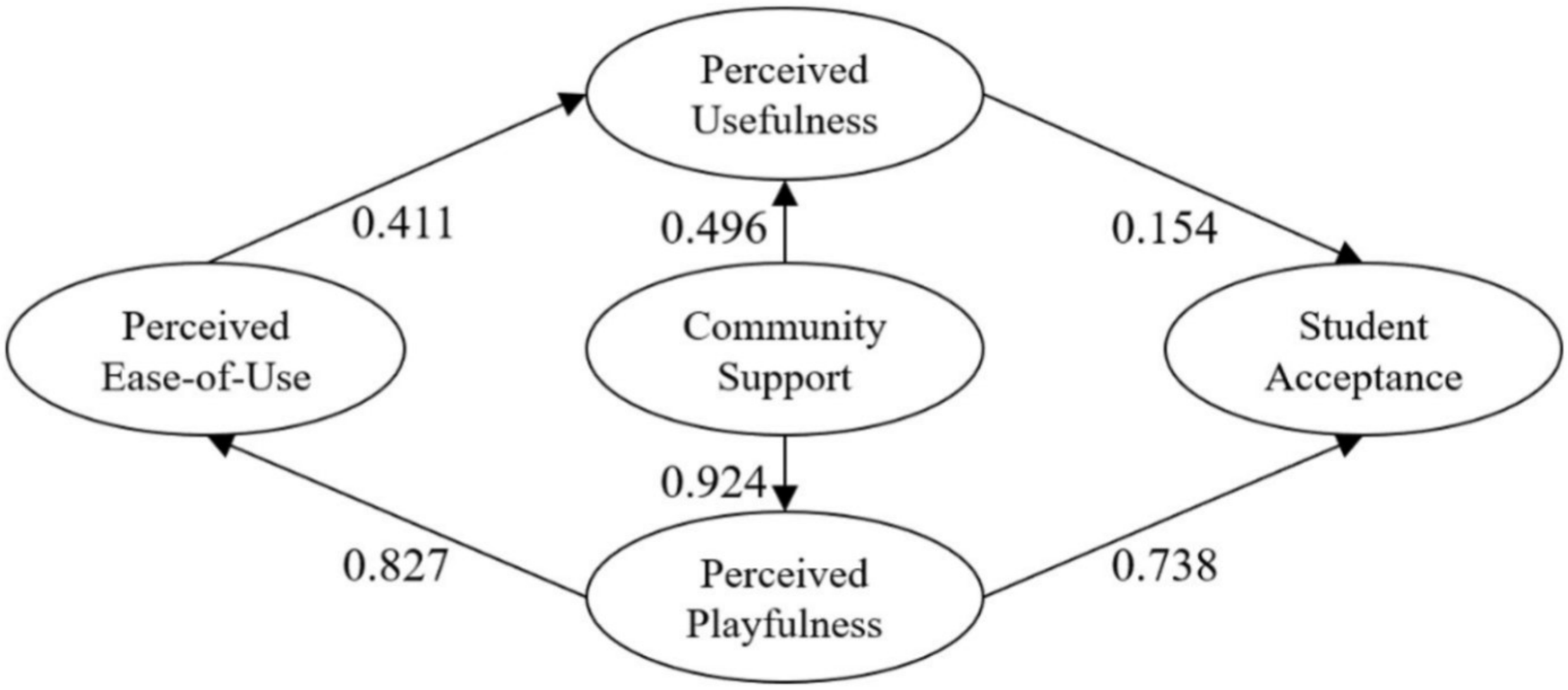


Fig. 11 The final model and path coefficients of primary science curriculum student acceptance of blended learning

Table 6 Influence of various latent variables on acceptance

Variables	Direct effect	Indirect effect	Total effect
PU	0.154	None	0.154
PE	None	$0.411 \times 0.154 = 0.063$	0.063
CS	None	$0.496 \times 0.154 + 0.924 \times 0.738 + 0.924 \times 0.82$	0.807

		$7 \times 0.411 \times 0.154 = 0.807$	
PP	0.738	$0.827 \times 0.411 \times 0.154 = 0.052$	0.790

The impact of latent variables on acceptance

According to the path coefficients in the final model, Table 6 lists the influence of each latent variable on the acceptance. The influence order for SA is CS > PP > PU > PE.

From the perspective of structural models, the most important factor that affects primary science curriculum SA of blended learning is CS. CS is the only exogenous variable, and it has direct and/or indirect effects on PP, PE, PU, and SA. CS has a great influence on PP, which shows that due to the characteristics of the age stage, PP in primary school students is mainly influenced by teachers, parents, classmates, and other external factors (for example, the community where the student lives). PP is also an important factor that affects acceptance, which reflects the disciplinary characteristics of science curriculum from one side. PP of blended learning in science curriculum not only has an obvious direct impact on SA, but also affects PU through PE, and then affects SA through PU.

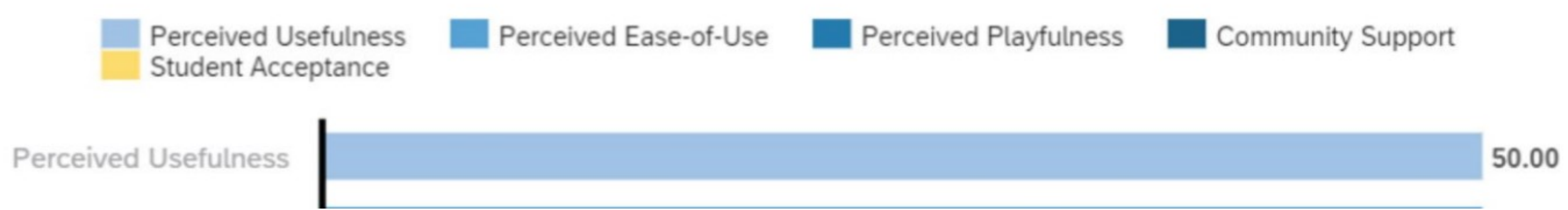
In the final model obtained in this study, neither PE nor PU shows strong influence on acceptance. This reflects the characteristics of the primary school students. Their acceptance standard of a new educational technology is not whether it is "easy to use" or "useful" like other groups, but mainly based on whether this technology is interesting and whether it is encouraged by surrounding teachers, parents and classmates.

Visual analytics

Build visualization application

There are still many primary school teachers who are not familiar with structural equation model. For teachers to use the final model more intuitively and improve their practices, a visualization application is preferred to demo the model and explain these influence factors. Current visualization tools usually support a powerful set of visualization types that can be used to design applications quickly (Xu, 2019).

SAP Analytics Cloud (SAC) is designed as an enterprise data analytics system (Choi & Ngo-Ye, 2019), and it contains a powerful designer which can be used to



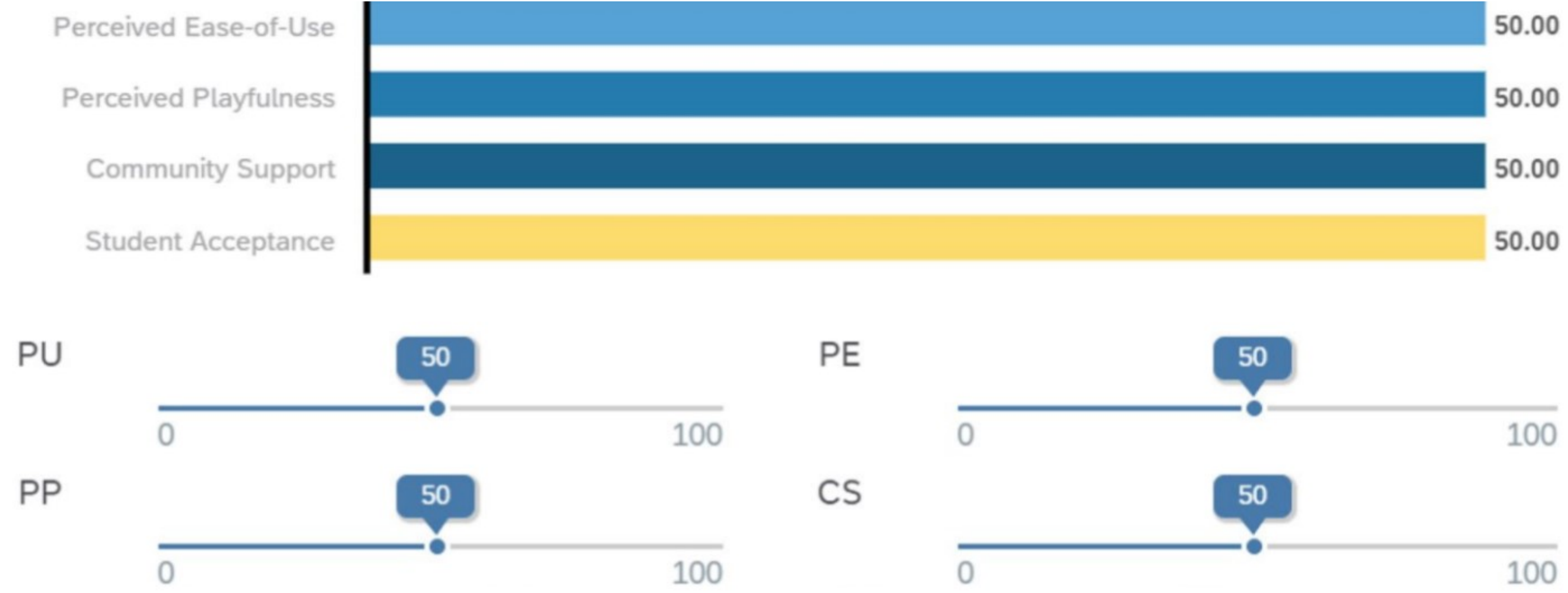


Fig. 12 Visualization Application GUI

design and implement visualization applications easily. SAC supports many visual controls which can be used to design the application, and users can use variables and scripts to change visualization effect dynamically to make a complicated application. In this case, to build a visual model according to M3, we can launch SAC analytics designer, use one bar chart to represent the 5 latent variables and use 4 slider controls to let users input values of PU, PE, PP, and CS. Figure 12 displays the initial GUI of visualization application for final model. Users can change the four sliders to change the 4 latent variables, and these changes will affect the value of SA.

Interactive visualization

To make the analytics application work, scripts and variables should be added to the SAC application. Each bar item of the Chart will be bound to one script variable and changing corresponding slider will update one or more variable values. Chart widget will be refreshed automatically to display these updated variable values. For

```
PU = PU + (CS - old_CS) * 0.496 + (CS - old_CS) * 0.924 * 0.827 * 0.411;
PU_S.setValue(PU);

PP = PP + (CS - old_CS) * 0.924;
PP_S.setValue(PP);

PE = PE + (CS - old_CS) * 0.924 * 0.827;
PE_S.setValue(PE);

SA = SA +( PU - old_PU ) * 0.154 + ( PP - old_PP ) * 0.738;
```

Fig. 13 CS slider on change event

Student Acceptance Model

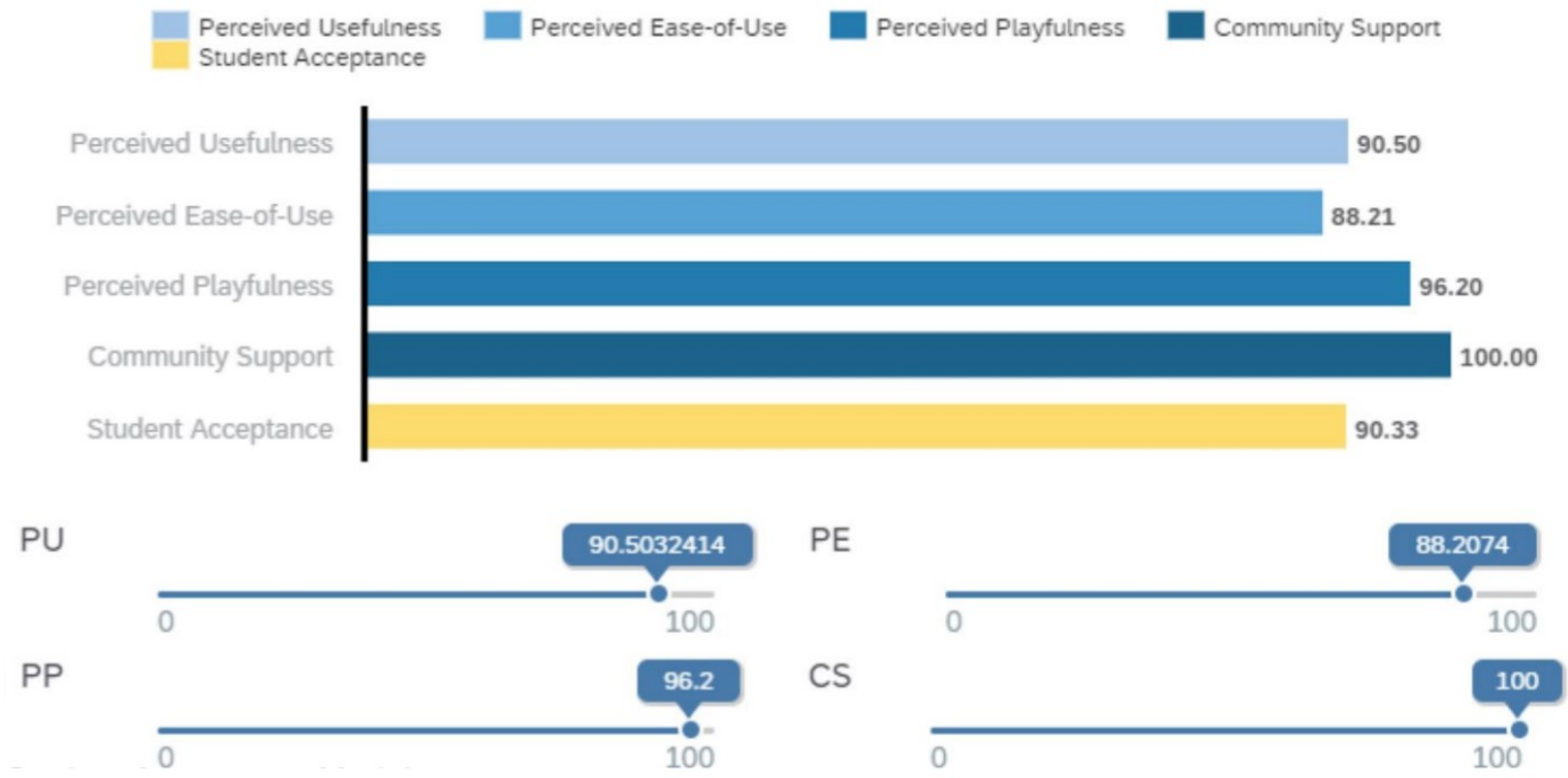


Fig. 14 CS slider value is changed to 100

example, onChange event of CS slider will execute following code to update PU, PP, and PE variables (old_CS is the original CS value. PU_S, PP_S, and PE_S are 3 variables for the 3 sliders) and update the 3 sliders. Figure 13 shows a part of the code.

If users drag and drop to change the CS slider value to 100, the application will update the bar chart and other sliders. SA value will be changed to 90.33, and the 3 other bar items (and corresponding sliders) will be changed as well according to script settings (CS can affect these variables). Figure 14 shows the change.

Fig. 15 PP slider value is changed to 100

If users change the PP slider value to 100, SA value will be changed to 89.52. It means PP factor has less impact than CS factor. And CS bar item is not updated (it is still 50), it means PP variable cannot affect CS variable. Figure 15 shows the case. Based on visual analytics technology and toolsets, the visualization application is easy to build and modified, which makes the theory model be understood and applied by more teachers. Using visual controls can explore existing models and improve visualization designs easily, and if the corresponding structural equation model is changed, visualization application can be updated quickly to align with theoretical model.

Conclusion

In primary science curriculum, if teachers want to improve the acceptance of students in the activity design of blended learning, it is very important to try to improve PP. PP is the intrinsic motivation for students to accept blended learning and satisfying the intrinsic motivation will significantly increase their willingness to use (Xu, 2018). In the teaching design of blended learning, according to the acceptance of students and the characteristics of the subject, more multimedia content such as pictures and videos and educational games can be used to bring students interesting ways (Montgomery et al., 2019). In order to improve SA, it is especially important to pay attention to the importance of CS. CS is the most influential factor, which indirectly affects students' attitudes through other factors. Everyone lives in a specific social environment, and the occurrence of personal behavior is greatly affected by the surrounding environment. For primary school students, they are young and do not have many social experiences, and their acceptance of blended learning is more susceptible to teachers and parents. In view of the powerful influence of CS, single SA of blended learning may also interact with the acceptance of teachers, parents, and peers. This aspect can be further studied. The structural equation model is a powerful research tool, and this research also proves if researchers can use visualization approaches to enhance the display effect, it can enable primary school teachers to better understand and apply the research results.

This research reveals that the behavior of teachers themselves is a significant part of CS and has a decisive influence on students' learning. First, teachers' knowledge needs to be continuously updated. In the current primary school, the technical skills and theoretical literacy of some science teachers need to be improved. With the rapid development of science and technology, artificial intelligence, visual programming, and other emerging technology fields are constantly being included in the primary school curriculum, so it is necessary to strengthen the training and education of science teachers. Secondly, to stimulate students' interest, schools need to be equipped with various types of teaching resources. In the requirement of resources, science, technology, and engineering education are significantly different from many liberal arts courses. For example, the teaching of material, life, earth, and cosmic sciences needs the support of various instruments, laboratories, etc., and the teaching of technology and engineering requires the use of workshops and computer rooms. Third, from the perspective of curriculum development, the most popular development in science curriculum education technology nowadays is virtual laboratory technology, which deserves the focus of blended learning platform developers. The virtual laboratory combines virtual reality (VR) technology and network technology, which greatly reduces the cost of experiments, and increases the interest in scientific experiments. VR is expected to significantly improve the learning approaches of science curriculum.

Structural Equation Modeling is based on linear assumptions (the relationship between the two factors is linear). This is a simplification of the real world, so when the value of the variable changes greatly, it may be necessary to remodel. The questionnaire survey method is indeed a research method widely used in researches of education and psychology, but this study found that network questionnaire has certain limitations in reflecting the reality. In survey practice, due to the large gaps in education informatization in various regions and schools, if the surveyed students do not understand blended learning at all, they tend to give up answering the questionnaire completely, which makes the collected data not representative of all students' opinions. Schools and families are increasingly aware of the data privacy protection of primary school students. The online communities and offline locations where primary school students gather are difficult for ordinary people to enter unless teachers or parents allow. This makes it difficult for researchers to interact with primary school students. Because of the limitation of the educational level of primary school students (especially the lower grades of primary school students are still lacking in reading and comprehension), the questionnaire survey method may not reflect the true thoughts of the respondents in all grades and regions. In future research, it may be necessary to obtain data from various aspects. Online learning platforms can be used as an objective data collection tool. At the same time, interviews and teaching experiments can be used as much as possible to collect samples in multiple dimensions. Building a visual analytics application to consume theoretical models for teachers is still a tentative practice. More building tools and designers should be applied to develop new applications quickly.

Acknowledgements The author would like to thank teachers and students of Institute of Vocational Education, Tongji University, especially Prof. Dr. Yue, CAI for his guidance on educational theory and statistics, and Ms. Gao-Le, LI for her assistance in collecting survey data for this paper.

Author contributions The main contribution of the author in the paper is designing one new structural equation modeling for primary science curriculum students and using collected survey data to improve and verify the model. The author also gives one new visual analytics approach to explore the structural model interactively.

Data availability The data that support the findings of this study are openly available in IEEE DataPort at http://doi.org/10.21227/kx61-7732, reference (Xu., 2020).

Declarations

Conflict of interest In accordance with my ethical obligation as a researcher, I am reporting that I have business interests in a company that may be affected by the research reported in the enclosed paper.

References

Alam, M. S. (2015). Effect of community factors on primary school learners' achievement in rural Bangladesh. *Journal of learning for Development*. http://hdl.handle.net/11599/870

Al-Azawei, A., Parslow, P., & Lundqvist, K. (2017). Investigating the effect of learning styles in a blended e-learning system: An extension of the technology acceptance model (TAM). *Australasian Journal of Educational Technology*. https://doi.org/10.14742/ajet.2741

Alshurideh, M., Salloum, S. A., Al Kurdi, B., & Al-Emran, M. (2019). *Factors affecting the social networks acceptance: an empirical study using PLS-SEM approach*. Paper presented at the Proceedings of the 2019 8th international conference on software and computer applications.

Bateson, P., Bateson, P. P. G., & Martin, P. (2013). *Play, playfulness, creativity and innovation*. Cambridge University Press.

Bentler, P. M. (1992). On the fit of models to covariances and methodology to the Bulletin. *Psychological Bulletin, 112*(3), 400–404. https://doi.org/10.1037//0033-2909.112.3.400

Bliuc, A.-M., Casey, G., Bachfischer, A., Goodyear, P., & Ellis, R. A. (2012). Blended learning in vocational education: Teachers' conceptions of blended learning and their approaches to teaching and design. *The Australian Educational Researcher, 39*(2), 237–257. https://doi.org/10.1007/s13384-012-0053-0

Chen, W. S., & Yao, A. Y. T. (2016). An empirical evaluation of critical factors influencing learner satisfaction in blended learning: A pilot study. Universal Journal of Educational Research, 4(7), 1667–1671. https://doi.org/10.13189/ujer.2016.040719

Choi, J. J., & Ngo-Ye, T. L. (2019). Selecting enterprise applications for curriculum: Insights from a teaching initiative. *Issues in Information Systems, 20*(1), 195–203.

Choo, J., & Liu, S. (2018). Visual analytics for explainable deep learning. *IEEE Computer Graphics and Applications., 38*(4), 84–92. https://doi.org/10.1109/ACCESS.2019.2923736

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Donaldson, R. L. (2011). Student acceptance of mobile learning. *Dissertations & Theses—Gradworks, 62*(12), 4763–4766.

Dwivedi, Y. K., Mustafee, N., Carter, L. D., & Williams, M. D. (2010). *A bibliometric comparison of the usage of two theories of IS/IT acceptance (TAM and UTAUT)*. Paper presented at the AMCIS.

Estriegana, R., Medina-Merodio, J.-A., & Barchino, R. (2019). Student acceptance of virtual laboratory and practical work: An extension of the technology acceptance model. *Computers & Education, 135*, 1–14.

Grossmann, S. D., Moura, M. D., Matias, M. D., Paiva, S. M., & Mesquita, R. A. (2018). The use of social networks in scientific research with questionnaires. *Brazilian Journal of Oral Sciences., 17*, e18162.

Huang, J., Lin, Y., & Chuang, S. (2007). Elucidating user behavior of mobile learning—a perspective of the extended technology acceptance model. *The Electronic Library, 25*(5), 585–598. https://doi.org/10.1108/02640470710829569

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191–204. https://doi.org/10.1016/S0378-7206(01)00143-4

Li, C., He, L., & Wong, I. A. (2021). Determinants predicting undergraduates' intention to adopt e-learning for studying English in Chinese higher education context: A structural equation modelling approach. *Education and Information Technologies., 26*, 4221–4239.

Lin, C. P., & Anol, B. (2008). Learning online social support: An investigation of network information technology based on UTAUT. *Cyberpsychology & Behavior the Impact of the Internet Multimedia & Virtual Reality on Behavior & Society, 11*(3), 268–272. https://doi.org/10.1089/cpb.2007.0057

Liu, Q., Yang, H., Ba, S., Wang, Y., & Zhao, W. (2019). Blended learning using mobile APP in secondary vocational instruction: design and implementation. In *Proceedings of the 10th international conference on e-education, e-business, e-management and e-learning* (pp. 189–193). https://doi.org/10.1145/3306500.3306544

Liu, Y., Li, H., & Carlsson, C. (2010). Factors driving the adoption of m-learning: An empirical study. *Computers in Education, 55*(3), 1211–1219. https://doi.org/10.1016/j.compedu.2010.05.018

Marchewka, J. T., & Kostiwa, K. (2007). An application of the UTAUT model for understanding student perceptions using course management software. *Communications of the IIMA, 7*(2), 10.

Means, B., Toyama, Y., Murphy, R., & Baki, M. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teachers College Record, 115*(3), 1–47.

Montgomery, A. P., Mousavi, A., Carbonaro, M., Hayward, D. V., & Dunn, W. (2019). Using learning analytics to explore self-regulated learning in flipped blended learning music teacher education. *British Journal of Educational Technology, 50*(1), 114–127. https://doi.org/10.1111/bjet.12590

Padilla-Meléndez, A., del Aguila-Obra, A. R., & Garrido-Moreno, A. (2013). Perceived playfulness, gender differences and technology acceptance model in a blended learning scenario. *Computers & Education, 63*, 306–317.

Picciano, A. G., Dziuban, C. D., & Graham, C. R. (2013). *Blended learning: Research perspectives* (Vol. 2). Routledge.

Pitafi, A. H., Kanwal, S., & Khan, A. N. (2020). Effects of perceived ease of use on SNSs-addiction through psychological dependence, habit: The moderating role of perceived usefulness. *International Journal of Business Information Systems., 33*(3), 383–407.

Powell, A., Watson, J., Staley, P., Patrick, S., Horn, M., Fetzer, L., …Verma, S. (2015). *Blending learning: The evolution of online and face-to-face education from 2008–2015*. Promising practices in blended and online learning series. International Association for K-12 Online Learning.

Rabu, S. N., & Talib, Z. (2017). The effects of digital game-based learning on primary school students' English vocabulary achievement and acceptance. *Innovative Teaching and Learning Journal (ITLJ)., 1*(1), 61–74.

Sani, A., Khristiana, Y., Zailani, A. U., & Husain, T. (2020). E-business adoption models in organizational contexts on the TAM extended model: A preliminary assessment. In *2020 8th International conference on cyber and IT service management (CITSM)*, 232020 October (pp. 1–5). IEEE.

Shimizu, S., & Kano, Y. (2008). Use of non-normality in structural equation modeling: Application to direction of causation. *Journal of Statistical Planning and Inference, 138*(11), 3483–3491. https://doi.org/10.1016/j.jspi.2006.01.017

Thompson, B. (2000). *Ten commandments of structural equation modeling*. American Psychological Association.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Walny, J., Frisson, C., West, M., Kosminsky, D., Knudsen, S., Carpendale, S., & Willett, W. (2019). Data changes everything: Challenges and opportunities in data visualization design handoff. *IEEE Transactions on Visualization and Computer Graphics., 26*(1), 12–22.

Wang, Y., Wu, M., & Wang, H. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology, 40*(1), 92–118. https://doi.org/10.1111/j.1467-8535.2007.00809.x

Williams, M., Rana, N., Dwivedi, Y., & Lal, B. (2011). Is UTAUT really used or just cited for the sake of it? A systematic review of citations of UTAUT's originating article. In 19th *European conference on information systems*, Helsinki, Finland, 9–11 June 2011.

Xinni, J., Zhangyi, W., Dongwei, W., & Yan, L. (2015). Comparison of GLS and WLS method based on measurement model of structural equation modeling. *Chinese Journal of Public Health, 31*(01), 104–108. (in Chinese).

Xiong, Y., Li, H., Kornhaber, M. L., Suen, H. K., Pursel, B., & Goins, D. D. (2015). Examining the relations among student motivation, engagement, and retention in a MOOC: A structural equation modeling approach. *Global Education Review, 2*(3), 23–33.

Xu, L. (2018). Exploring MOOC Design for musical instrument education. *Digital Education, 4*(04), 17–22. https://doi.org/10.3969/j.issn.2096-0069.2018.04.003 (in Chinese).

Xu, L. (2019). User story based information visualization type recommendation system. *International Journal of Information Engineering and Electronic Business, 11*(3), 1–7. https://doi.org/10.5815/ijieeb.2019.03.01

Xu, L. (2020). Student acceptance of blended learning - primary science curriculum – China. https://ieee-dataport.org/open-access/student-acceptance-blended-learning-primary-science-curriculum-china. https://doi.org/10.21227/kx61-7732

Yongjun, J., & Xin, L. (2020). Characteristics analysis of teachers' online learning behavior supported by learning analytics. *China Educational Technology, 11*(2), 75–82. (in Chinese).

Zacharis, N. Z. (2015). A multivariate approach to predicting student outcomes in web-enabled blended learning courses. *The Internet and Higher Education, 27*, 44–53. https://doi.org/10.1016/j.iheduc.2015.05.002

Zhai, X., & Shi, L. (2020). Understanding how the perceived usefulness of mobile technology impacts physics learning achievement: A pedagogical perspective. *Journal of Science Education and Technology., 29*(6), 743–757.

Zhang, Z., Cao, T., Shu, J., & Liu, H. (2020). Identifying key factors affecting college students' adoption of the e-learning system in mandatory blended learning environments. *Interactive Learning Environments.* https://doi.org/10.1080/10494820.2020.1723113

Xu Liu is currently a senior software developer in Business Intelligence department of SAP Labs China in Shanghai. He has received his Bachelor of Management degree from Nanjing University and his Master of Natural Science degree from Peking University. He has participated in feature design and development of multiple enterprise software products including SAP Crystal Reports, SAP Lumira, SAPUI5, and SAP Analytics Cloud. As the first author, he has published 10 academic journal papers. His research interests include Business Intelligence, Visualization, Software Engineering, and Educational Technology.