International Journal of Innovative Research and Scientific Studies, 5(3) 2022, pages: 170-183

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Evaluation of a Software Model for Integrating Learning Management Systems and Massive Open Online Courses

Talent T. Rugube[1*], Desmond Govender[2]

[1,2]*Computer Science Education, University of KwaZulu Natal, Durban, South Africa.*

* Corresponding author: Talent T. Rugube (*Email: ttrugube@gmail.com*)

Abstract

Educational technology is widely used in higher education. The implementation requires the integration of learning systems. The integrated systems can be evaluated to see if they assist learners in achieving learning outcomes by interacting with relevant content. The study focused on inferential statistics arising from the technology acceptance evaluation of a software design model. The proposed software design model automatically combines data to integrate a Learning Management System (LMS) with Massive Open Online Courses (MOOCs). The inferential statistics explain the acceptance or rejection levels of the software design model by the stakeholders (lecturers, students, and universities at large) based on the Technology Acceptance Model and Task-Technology Fit. Google forms were used to obtain information on the software design model. Partial least squares structural equation modelling was applied for data analysis because the data were non-normally distributed. The study's results showed that Task-Technology Fit constructs had a significant effect on the technology acceptance model. The three constructs influencing use that emerged from this study were, in order of importance: perceived usefulness, perceived ease of use, and intention to adopt. Perceived usefulness was the most powerful construct due to its total effect size, proving the importance of useful technology in the higher education setting.

Keywords: Design model, Integrated learning systems, Technology acceptance, Task technology fit, Learning management systems, Massive Open Online Courses, Partial least squares.

DOI: 10.53894/ijirss.v5i3.493
Funding: This study received no specific financial support.
History: Received: 8 April 2022/**Revised:** 17 June 2022/**Accepted:** 30 June 2022/**Published:** 22 July 2022

Authors' Contributions: Both authors contributed equally to the conception and design of the study.
Competing Interests: The authors declare that they have no competing interests.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained.
Ethical: This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

In recent years, educational technology has become an increasingly widespread approach in higher education institutions globally [1]. Universities are equipping themselves with LMS to avail not only a common platform for course management and delivery, but also one that can be integrated with other repositories where students can access relevant content. In many cases, the aim is to enhance the way teaching and learning take place in universities, from the nonautomated ways content is obtained to an automated way of content presentation. However, change takes time to be accepted. Despite the benefits offered by LMS, MOOCs, and digital learning platforms, users can either accept or reject the technologies [2]. Acceptance in this context is how users engage with technology. Earlier studies showed that when technology is availed, users are expected to show their willingness to use the technology [3]. However, this has not always been the case with LMS.

A study using the Technology Acceptance Model (TAM) by Maramba and Mazongonda [4] showed that lecturers and students in most of these institutions were reluctant to implement digital teaching and learning technologies due to limited skills and ignorance of the resources offered which, in turn, promoted negative attitudes [5]. Reluctance is credited, informally though, to discouragement and frustrations arising from the economic situation in developing countries regarding regulated access to electronic services [6].

As universities implement the use of LMS, the selection, uploading, updating, and removal of content is the right of administrators and editing teachers of the modules [7]. As a result, the quality of content exposed to students relies subjectively on the lecturers' engagement with new content, and with the LMS. The lecturers manage all sorts of content and activities deployed on these learning management systems, including the sequencing, importing, and exporting of files and folders. The proposed design model is envisioned to fit within the existing contexts of LMS and MOOCs.

Since some institutions do not exploit all the LMS features, this paper aims to present the approach adopted to evaluate the impact of the implementation of a design model for integrating MOOCs and LMS on digital platforms in higher education. The aim is to design a system that automatically feeds into an LMS, allowing maximum resources to be made available to students. Such a model would likely foster automated content selection and uploading, free from administrators' and editing teachers' interventions. It would likely validate content sequencing and automatically verify content pre-requisites for enhanced teaching and learning. In this study, the researchers resort to embracing MOOCs' introduction into teaching and learning as optional resources with up-to-date content relevant to different learning areas.

Given these propositions, the design model in question was not seen just as a new integration approach platform for use by lecturers and students, but as a complex environment comprising the technological platform and the related learning materials. The researchers explored formative evaluation, which is aimed at eliciting critical issues and identifying ways for further development of the design model itself. To achieve this, the paper describes the evaluation tasks that were performed. It also describes the TAM and Task Technology Fit (TTF) model used as a strategy to evaluate the software design model. The hope was to come to a point where the software design model was certified according to the functional requirements set. Detailed procedures for statistical validation were demonstrated using the partial least squares path modeling (pls-pm). In this context, partial least squares path modeling is a multivariate technique that combines causal modeling with data analysis features [8].

The researchers proposed to design and recommend a hybrid technology adoption model to serve as a tool in university policymaking. The quality of the design model was evaluated by software engineering experts through a combined TTF model and TAM model. The TTF model and TAM are adopted and used together with the design science research framework. The relevance cycle of the design science research, being the first cycle, stipulates requirements for the study and defines evaluation methods of the software model [9] presenting an argument that, besides technology being accepted freely, it must be suitable for its intended users and match their activities to show its efficiency. TTF was adopted in this study since it is a model that articulates why a set of technology is used for a particular task. If the task characteristics and technology characteristics are aligned, then the technology is used better.

A literature review and conceptual framework are presented in the next section, emphasizing attempts made, so far, in the evaluation of design models. The research methodology is explained before data analysis and results are presented. A discussion of our findings follows. We then conclude the paper, highlighting the main observations, the contributions emanating, as well as plans and limitations.

2. Literature Review

Studies related to design models have been done [8]. Technically, a design model is the implementation of a functional information system comprising design subsystems, collaborations and relationships between them. A model is defined as a microcosm of a real object which can be used in calculations [10]. In one study, a model was designed based on educational technologies for open learning environments [11].The model presented integrated existing learning environments with open technologies and practices [12] and introduced a conceptual model that integrates several learning management systems to fulfill educational requirements.

Technological advances continue to provide more ways of interaction whilst at the same time offering potential opportunities for teaching and learning. The present learning environment needs continued innovations which in turn result in obtaining the desired learning goals. This leads to the need for developing innovations in the use of learning platforms, to facilitate the sharing of relevant information among students.

The study focuses on the development of logical designs of the proposed software design model and assesses their acceptance, both at the unit and integrated or functional levels. In each case, as proposed in design science methodology, component units are developed to improve the functional angle of the software design model. Therefore, researchers used an extended version of the technology acceptance model to study the acceptance of the design model.

Past research [9] reveals that novel models designed for innovation should be accompanied by evaluation approaches that can appreciate any change in a digital learning system. This study focuses on assessing the acceptance of a software design model at integrated and functional levels. The researchers used an extended version of the TAM to study the acceptance of the design model. TAM is an information systems theory that illustrates how users are caused to accept and apply a certain technology [9]. It shows that when users are presented with new technology, they are met with factors that influence their decision on how and when to use the technology [12].

A study by Osterwalder [9] reveals that TAM is the most dominant, commonly active, and highly predictive model of information technology adoption. This study takes advantage of the fact that the use of TAM is valuable as it has been applied in education research.TAM has been used before in support of e-learning use and acceptance [12] and MOOCs [13]. Though TAMs are widely used, the model has some known weaknesses. It has been reported that the TAM model does not include specific task aspects [14]. Other studies show that TAM lacks relevance in the information technology domain [15] . It is thus worthwhile for this work to look at another theory that focuses on task aspects, particularly, TTF.

2.1. Conceptual Framework

TTF in this study is defined as the measure at which a system ties with interests, fits with tasks, and meets needs [16]. TTF emphasizes individual impact which refers to improved efficiency, effectiveness, and or higher quality [12]. As shown in Figure 1, this model is suitable for investigating the actual usage of the technology, especially testing new technology to get feedback.

The TAM theory describes how users come to accept and use technology [12]. TAM is designed to ascertain usage prediction [16]. The concept of acceptance which flows from a stimulus through response shows how an artifact's features and capabilities influence end users' motivation to use the application, and finally how the actual system is used as shown in Figure 1 [17].

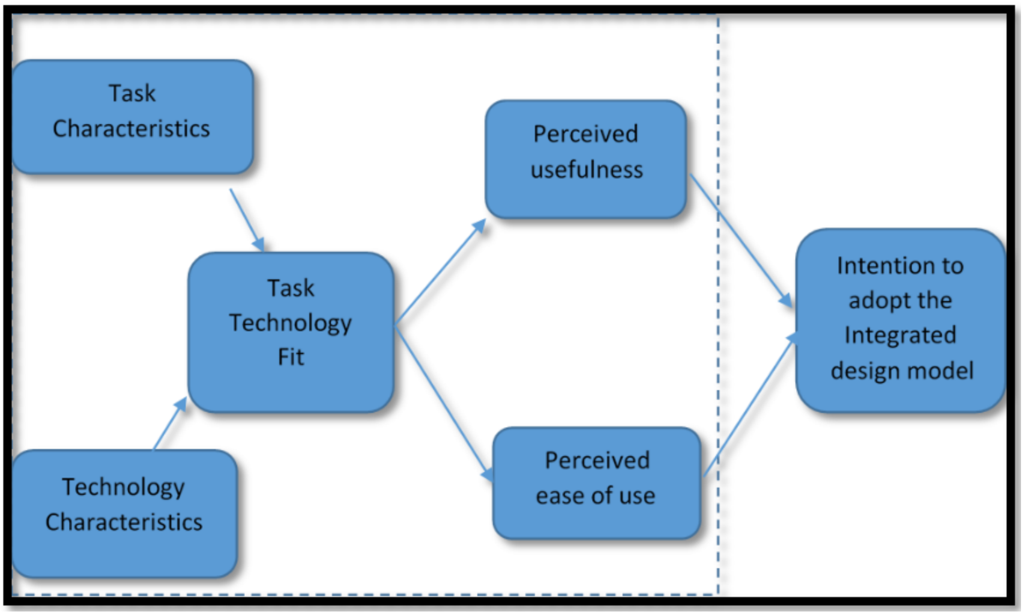

Figure 1.
TAM-TTF model.

In this study, the researchers added the TTF model to the TAM to evaluate the impact of the design model on policy-making in universities.TTF extends TAM by considering how the task affects us, as in how well the new technology fits the requirements of a given task. The hybrid of TAM and TTF provides a clearer understanding of MOOCs [16]. The TTF model compensates for the limitations of the TAM. TAM aims to recognize how beliefs and attitudes influence the behavior of users' use of technology. TTF extends TAM in Figure 1 by considering how a task will affect the use of information systems technology.

The next sub-sections describe factors for assessing the intention to adopt the design model.

2.2. Task Characteristics

Task performance is considered to be a measure of the success of a technological artifact [18]. Accordingly, the researchers integrated the TAM and TTF for exploring factors that explain software utilization and its links with user performance [18]. In this study, task refers to content uploading processes and related activities. Learning content sharing is one task that can be accomplished through the implementation of integrated designs. Based on the results of these studies, the following hypothesis was derived:

H_1: Technology Acceptance Model predicts intention to adopt the design model.

2.3. Technology Characteristics

The task-technology fit model reflects the significance of fitting the features of technology used to the requests occasioned by individual needs [19]. In this study, technology refers to any software tools used by lecturers and students in carrying out the tasks for accessing and uploading content. Within this framework, the following hypothesis has been formed:

H_2: Task characteristics of the design model are positively related to Task Technology Fit.

2.4. Perceived Usefulness

In the digital learning systems domain, perceived usefulness is a common factor employed in technology acceptance model studies [20]. As such, perceived usefulness is the degree to which a system user is certain that the technology would improve the execution of their tasks [21]. The same author further attests that perceived usefulness is also influenced by perceived ease of use as well as intention to use. In this study, the researchers propose that the usefulness of a system in educational technology is interrelated to how lecturers use the available tool to make learners interact with content. Lecturers and students would make use of new technology if it assists them in obtaining their learning goals. The following hypothesis has been formed:

H_3: Technology characteristics of the design model are positively related to Task Technology Fit.

2.5. Perceived Ease of Use

Perceived ease of use refers to the degree to which an individual trusts that using the technology will not be difficult or challenging [21]. It is an evaluation of the degree to which users achieve their tasks with ease [22]. Otherwise, they will stick to their old methods instead of using the new system. This is like Osterwalder [9] their study showed that Perceived Ease of Use had a significant influence on attitude and a strong influence on Perceived Usefulness. Perceived Ease of Use is an important secondary determinant of intentions. Moreover, perceived Usefulness had a direct significant effect on the intention to use computers [22]. Considering all these findings in the relevant literature, the hypothesis describing the relationship between perceived trust and attitudes towards online learning is presented below:

H_4: Task technology fitness has an impact on the Technology Acceptance of the design model.

2.6. Intention to Adopt

The technology could be adopted by an institution because they are ready for it and are satisfied with its features [23]. This would probably determine the extent to which the technology is fully utilized. In this study, the intention to adopt may be understood as the intention to implement the integrated design model. In this context, it is possible to put forward the following hypothesis:

H_5: Perceived usefulness of the design model has an impact on the intention to adopt the model.

2.7. Task Technology Fit

The task characteristics and technology characteristics, both impact the task-technology fit construct as depicted in Figure 1. The task-technology fit construct ultimately affect the final deliverable, which is task utilization [24]. In this study, the construct of TTF articulates the capability of digital technologies to support teaching and learning tasks. When technology fits the task requirements, then there is a high likelihood that it will be adopted. To this extent, it is plausible to suggest the following hypothesis:

H_6: Perceived ease of use of the design model has an impact on intention to adopt the model.

3. Research Methodology

The design model was assessed by exhibiting it to potential integrated LMS users who were software engineering practitioners and computer science students who had taken a software engineering course. An artifact's evaluation is a method of determining its utility. [25]. Participants in this study analyzed the artifact before responding to an online questionnaire with their thoughts. The TTF components and the technology acceptance model were used to create the questionnaire. The study's research model determined the minimum required sample size [26] . A total of 117 people were included in the final sample. Some people answered, but others did not, most likely due to power disruptions and the high cost of internet connection. The TAM [27] as well as the TTF model were used to structure the survey instrument. Task characteristics, technological attributes, perceived utility, intention to adopt, perceived ease of use, and TTF were all addressed in the models.

SPSS version 23 and R version 3.6.1 were used in the analysis. For descriptive statistics, SPSS was utilized. R is a free open-source data analysis program that was primarily utilized for pls-pm. The pls-pm is also useful for commands, pathway editing, and graphics on inner and exterior models. R software makes it simple to create associations between latent variables (inner model), indicators (outer model), and the bootstrapping technique. The next section contains graphics, pathway directions, conclusions, limitations, and recommendations.

Table 1.
Participants by qualification.

Variables		Frequency	Percent	Valid Percent
Valid	Bachelors	87	74.4	75.7
	Masters	21	17.9	18.3
	Doctorate	7	6.0	6.1
	Total	115	98.3	100
Missing	System	2	1.7	
Total		117	100	

Table 2.
Participants by gender.

Variables		Frequency	Percent	Valid Percent
Valid	Male	86	73.5	74.1
	Female	30	25.6	25.9
	Total	116	99.1	100
Missing	System	1	0.9	
Total		117	100	

3.1. Data Presentation

The analysis began by looking at the demographic statistics of respondents in the research. From Table 1 to Table 2 the greater proportion of respondents were undergraduate students made up of 87 out of 117, which was 75.6%; and 86 out of a total of 117 respondents were male, which constituted 74.1%. Responses from the technology adoption form were mostly based on Technology Acceptance Model and Task Technology Fit models.

3.2. Combined Technology Acceptance Model and Task-Technology Fit Analysis

The pls-pm, a statistical data analysis tool found at the confluence of Regression Models, Structural Equation Models, and Multiple Table Analysis methods, was used to evaluate the design model.

Task Characteristics, Technology Characteristics, Task Technology Fit, Perceived Usefulness, Perceived Ease of Use, and the Intention to Adopt Model are the six variables or factors examined in this study. Variables that are observable or observed are present in each construct. Variables in the manifest can be measured or observed. The pls-pm is divided into two parts: the measurement model (also known as the outer model), which looks at relationships between latent variables and manifest variables, and the structural model (also known as the inner model), which looks at relationships between latent variables (LR).

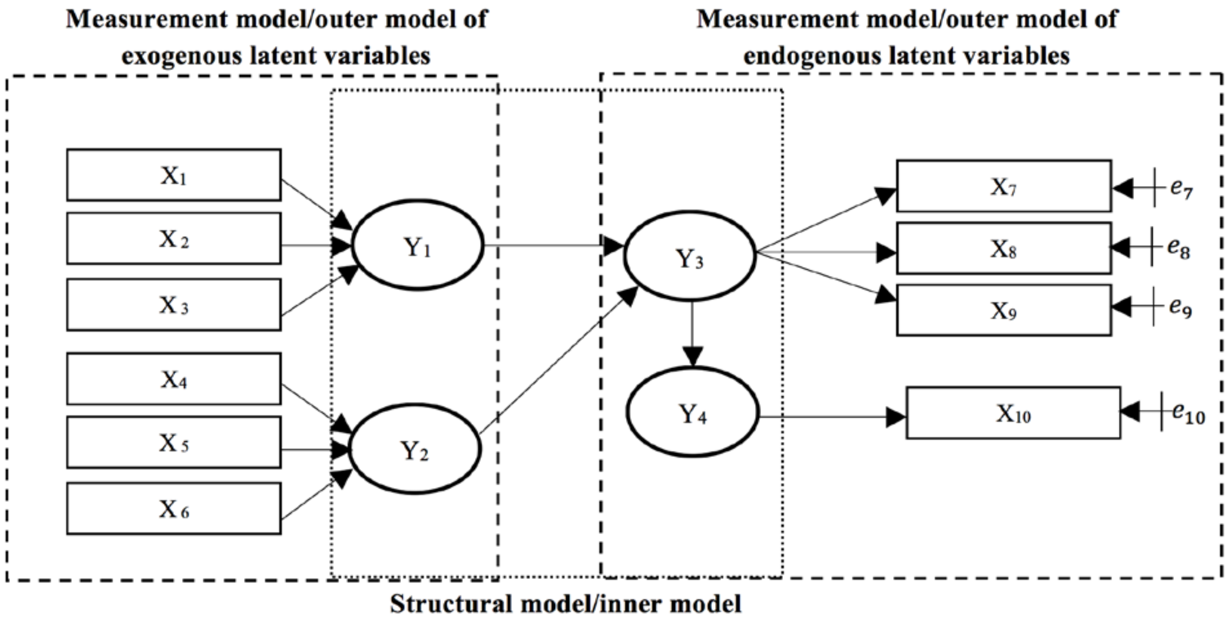

Figure 2.
An example of a path model [8].

Diagrams are employed in path models to convey a visual impact of hypotheses and theory-based relationships among variables. In Figure 2, the manifest variables are labeled X1 through X10 indicators, while the latent components are labeled Y1 through Y4. The error terms E7 through E10 are related to an endogenous construct whose values are governed by other variables [29].

The latent variables (constructs) are measured according to the measuring theory. In the structuring equation domain, there are two measurement scales: reflective and formative. In the literature, the reflexive indicators are the most commonly employed [29]. 'Perceived ease of use' [28] is a common example of a reflective paradigm in Information Systems research. The degree to which one believes using technology is simple is referred to as perceived ease of use. Six constructs (easy to learn, controllable, clear and understood, adaptable, easy to become, and easy to use) are also used to assess perceived ease of use [29]. As a result, as perceived ease of use improves, all six metrics improve as well. All of the variables are assumed to be related.

Reflective metrics were used in the current study's analysis (Mode A). The current study's pls-pm analysis was divided into four sections:

- The original hypothesized framework Figure 1.

- The modified framework in which latent variables or blocks (Technology Task characteristics [Task_char] is an independent variable to Perceived Usefulness [Perc_usef], Perceived Ease of Use [Perc_eas], and Intention to adopt [Int_adop_mod]. Latent variables Task characteristics and Technology characteristics [Tech_char] are also independents for predicting Perceived Usefulness and Perceived Ease of use.
- Bootstrapping the original sample.
- Bootstrapping the modified model framework.

3.3. The Original Partial Least Squares Path Modeling Model Based on Figure 1

The main ingredients for the partial least squares path modelling function, pls-pm, were prepared to begin the process of building the pls-pm model (). The inner model, the list of blocks, and the vector modes make up the model's parameters. The inner model, which is presented in a matric format, is shown in Table 3.

Table 3.
The inner model: Path matrix.

Task_char [1]= c(0, 0, 0, 0, 0, 0)						
Tech_char = c(0, 0, 0, 0, 0,)						
Task_tech_fit=c(1, 1, 0, 0, 0 ,0)						
Perc_usef=c(0, 0, 1, 0, 0, 0)						
Perc_eas=c(0, 0, 1, 0, 0, 0)						
Int_adop_mod=c(0, 0, 0, 1, 1, 0)						
TAM_TTF_path						
Construct items	**Task_char**	**Tech_char**	**Task_tech_fit**	**Perc_usef**	**Perc_eas**	**Int_adop_mod**
Task_char	0	0	0	0	0	0
Tech_char	0	0	0	0	0	0
Task_tech_fit	1	0	0	0	0	0
Perc_usef	0	1	0	0	0	0
Perc_eas	0	0	1	0	0	0
Int_adop_mod	0	0	0	1	1	0

Note: TAM_TTF_path=rbind(Task_char,Tech_char, Task_tech_fit, Perc_usef, Perc_eas, Int_adop_mod).

To visualize the scenario, a path diagram for the inner model was created.

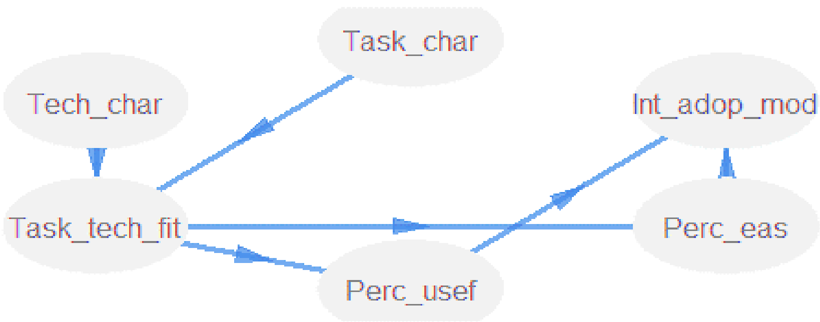

Figure 3.
Inner model with innerplot.

Figure 3 depicts a visual presentation of the inner model with innerplot.
The list identifying the blocks of the measurement (outer) model and the measurement type to be employed (in this case, reflective indicators) is the second ingredient for pls-pm ().

Table 4.
Unidimensionality of blocks.

Blocks Definition			
Block	**Type**	**Size**	**Mode**
1 Task_char	Exogenous	5	A
2 Tech_char	Exogenous	7	A
3 Task_tech_fit	Endogenous	6	A
4 Perc_usef	Endogenous	8	A
5 Perc_eas	Endogenous	4	A
6 Int_adop_mod	Endogenous	5	A

Each latent variable's and mode type's summary statistics is shown in Table 4.The size of a construct is proportional to the number of indicators or manifest variables it contains. For example, Task char has five indications. All latent-indicator associations are considered as reflecting, resulting in mode A. Some blocks/latents, such as Task char and Tech char, are handled as independents in the inner model analysis, but Task _tech fit is treated as a dependent variable for the first inner model prediction.

The quality of the measurement model is the first step in diagnosing a pls-pm model. In the analysis, reflective indicators were employed. In a reflective block, the manifest variables or indicators are thought to be caused by the hidden variable (i.e. reflective manifest variables are indicating the same latent variable).

A hidden variable that never emerges as a dependent variable is known as an exogenous variable. Otherwise it is referred to as an endogenous variable.

All latent-indicator associations are considered as reflecting, resulting in mode A. It's worth noting that some blocks or latents are handled as independents in the inner model analysis. Task and Technology features are among them, with Task technology fit being considered as a dependent variable in the initial inner model prediction. In addition, certain variables serve as both independent and dependent variables. Perceived usefulness and ease of use are also predicted by Task tech fit, which is an independent variable.

Figure 4 shows an inner plot of each block created by viewing the loadings/correlations. With red arrows on the corresponding markers PE1 and IA4, the two blocks, Perceived Ease of Use and Intention to Adopt, are troublesome. With their respective structures, they display negative loadings.

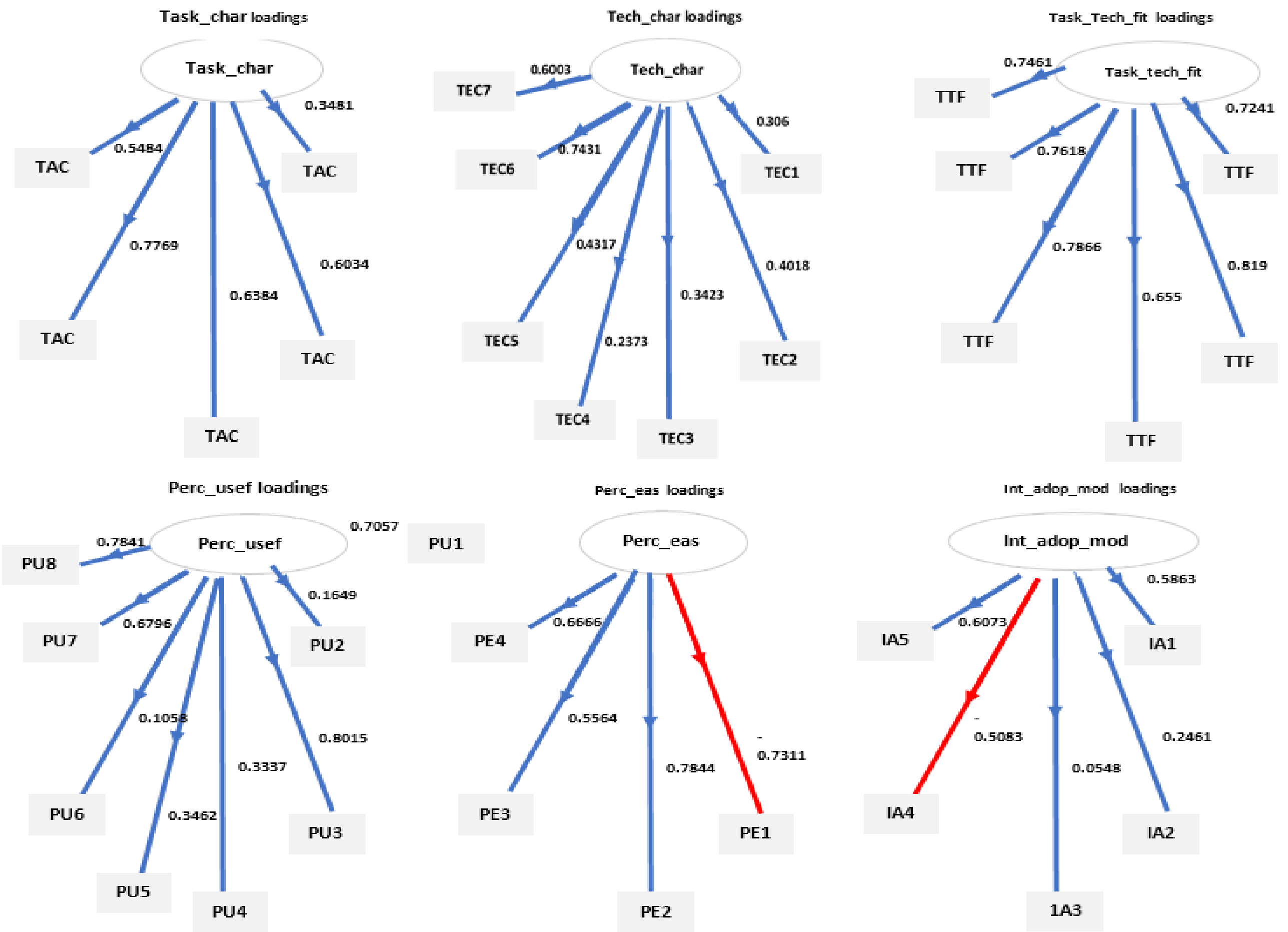

Figure 4.
Visualisation of loadings /correlations in each block.

3.4. Partial Least Squares-Path Modeling Round 2

The indicators should be updated: for example, a) I believe that searching for information on the platform does not need a lot of work and time (PE1) > Searching for information on the platform requires little effort and time (PE1a).

b) Universities would consider investing in implementation resources (IA4 > universities should invest in implementation resources (IA4a).

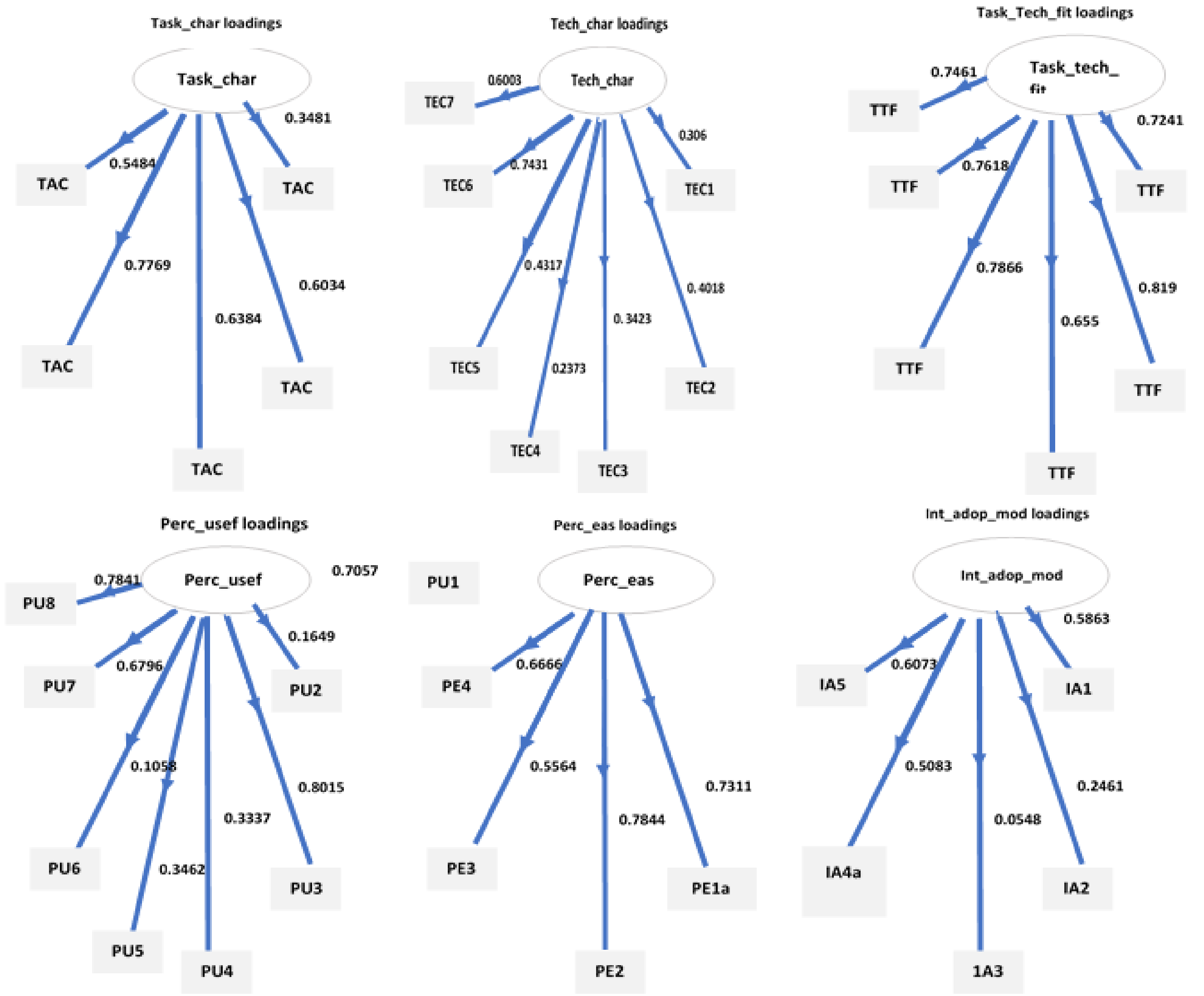

Figure 5.
Visualisation of loadings /correlations in each block.

Figure 5 shows that the arrows appear to point in one direction after redefining variables PE to PE1a and IA4 to IA4a. The results, on the other hand, reveal that variable IA3 has a low loading. It's also crucial to look at the cross-loadings at this stage.

3.5. Cross-Loadings

The loadings of indicators and associated latent variables are examined at this point to verify that trait indicators are eliminated. This is done with the remainder of the latent variables.

Cross-loadings of original path model variables, such as TEC4 (under technology characteristics block), PU2, PU4, PU5 (all under Perceived usefulness block), and IA3 (under Int to adop mod block), were presented as traitor variables because their loadings were less than loadings in a different block they link block to. Such variables should be removed from the equation. The next phase of analysis will look at both the inner (structural model) and outer (measurement model) models without include these variables.

3.6. Partial Least Squares Path Modeling Round 3: Dropping Traitor Variables

After eliminating the variables specified in the second round of the path model analysis, it can be seen that the variable PU6 has a low loading with its block, and it should be removed from the path modeling study. Round 3 is depicted in Figure 6 without traitor variables.

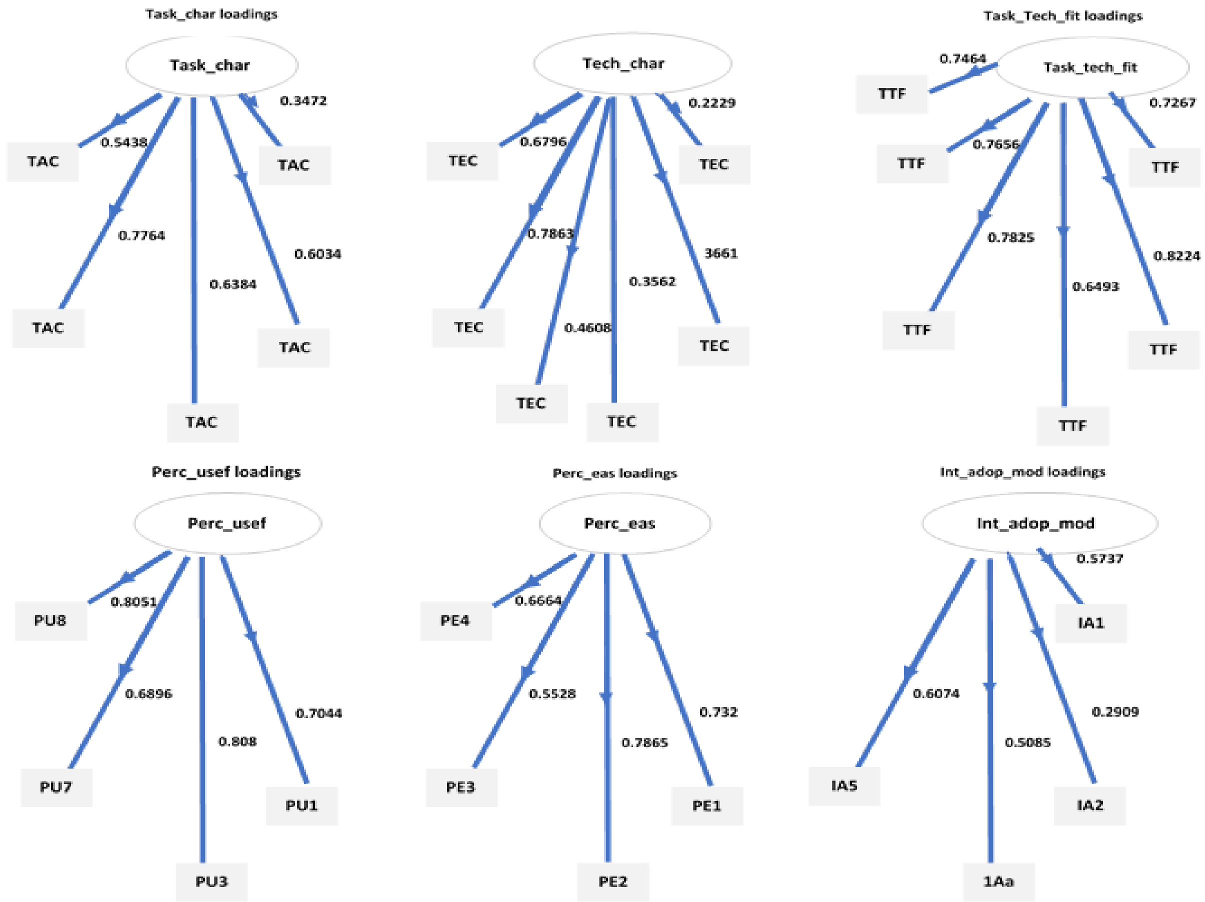

Figure 6.
Visualisation without 'traitor' loadings.

3.7. The Outer Model (Measurement Model)

The cross-loadings column removed the ambiguity of traitor variables. The outer model plot (measurement model) in Figure 6 no longer has indicators pointing in opposite directions. Most indicators have loadings of at least 0.45 in value and can be good.

3.8. The Inner Model (the Structural Model)

Except for the Int adop mod and Perc eas of use relationship, which is negative and insignificant since the p-value is higher than 0.05, the inner model analysis in Table 5 demonstrates that the associations between the latents are positive and significant because the p-values are less than 0.05. In these cases, the model is appropriate and preferable.

Table 5.
Inner model coefficients table results in inner model $Task_tech_fit.

Construct items	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	5.76E-17	0.077	7.49E-16	1.00E+00
Task_char	4.08E-01	0.0796	5.13E+00	1.22E-06
Tech_char	3.08E-01	0.0796	3.87E+00	1.84E-04
$Perc_usef				
Construct items	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	7.29E-18	0.076	9.59E-17	1.00E+00
Task_tech_fit	5.80E-01	0.076	7.64E+00	7.11E-12
$Perc_eas				
Construct items	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	4.88E-17	0.0812	6.01E-16	1.00E+00
Task_tech_fit	4.91E-01	0.0812	6.05E+00	1.88E-08
$Int_adop_mod				
Construct items	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	1.45E-16	0.0884	1.64E-15	1
Perc_usef	3.68E-01	0.1011	3.64E+00	0.000413
Perc_eas	-1.04E-01	0.1011	-1.03E+00	0.304112

3.9. Bootstrap Validation

Given that partial least squares path modeling is not based on any distributional assumptions, resampling techniques were used to predict typical errors and confidence intervals [7]. The bootstrap method is used to make such predictions. The partial least squares function (pls-pm) provides bootstrap resampling to get confidence intervals for evaluating the correctness of the partial least squares parameter estimates. So far, no bootstrap validation had been required because there was the need to first check that the results of the outer and inner models made sense. Resampling approaches were utilized to forecast typical errors and confidence intervals because partial least squares path modeling is not dependent on any distributional assumptions [7]. To make such forecasts, the bootstrap approach is utilized. Pls-pm() is a partial least squares function that uses bootstrap resampling to generate confidence intervals for assessing the accuracy of partial least squares parameter estimations. There had been no requirement for bootstrap validation so far because the outcomes of the outer and inner models had to be checked first.

4. Results

Bootstrapped results were obtained, for the outer weights, the loadings, the path coefficients, the R2, and the total effects. For each of the results shown, the study inspected the bootstrap confidence interval (95%). This was especially important for path coefficients. The path coefficients represent the direct effects between the domains performed according to the partial least squares path modeling approach.

Table 6 displays the original value that came out from the first partial least squares path modeling analysis, then compares the value Mean Bootstrapped value (mean. boot) with the bootstrap sample. The standard error (Std. error) is displayed to give an indication of the standard deviation and mean. Lower percentiles (perc.0.25) and upper percentiles (perc.975) of the 95% bootstrap confidence intervals are given to show the significance.

Table 6 showed that bootstrap intervals for the path coefficients of Tech_characteristics on both Task_Tech_fit and Perceived usefulness contain a zero since the confidence interval has negative values on the lower percentile. Also, Task_Tech_fit on Int_adop_mod and Perc_usef on Int_adop_model contained a zero in their confidence intervals; hence, the results are not significant at the 5% level. Other results that did not contain negative values were significant at 5%.

After an analysis of both the original model, modified model, and bootstrapped models, it was convenient to test the hypotheses based on the outer and inner models of the three models above. The hypotheses to be tested were as follows:

H1: Technology Acceptance Model predicts intention to adopt the design model.
H2: Task characteristics of the design model are positively related to Task Technology Fit.
H3: Technology characteristics of the design model are positively related to Task Technology Fit.
H4: Task technology fitness has an impact on the Technology Acceptance of the design model.
H5: Perceived usefulness of the design model has an impact on intention to adopt the design model.
H6: Perceived ease of use of the design model has an impact on intention to adopt the design model.

Model A: Original model

In this paper, six hypotheses formed the technology acceptance model and task-technology fit model to be used for evaluation of the software design model. In this section, each of the research hypotheses is discussed in light of the research analysis results. In Table 7, each hypothesized path effect was considered using the partial least squares path modeling path, coefficient and a measure of its statistical significance (see Table 6).

Table 6.
Bootstrapping results of the modified model.

Construct items	Original	Mean. Boot	Std. Error	perc.025	perc.975
Task_char->Task_tech_fit	0.40	0.41	0.11	0.22	0.62
Task_char->Perc_usef	0.22	0.26	0.14	0.01	0.51
Task_char->Perc_eas2	0.27	0.30	0.12	0.09	0.54
Tech_char->Task_tech_fit	0.32	0.26	0.24	-0.44	0.49
Tech_char->Perc_usef	0.07	0.06	0.12	-0.22	0.25
Task_tech_fit->Perc_usef	0.45	0.40	0.17	0.08	0.66
Task_tech_fit->Perc_eas2	0.36	0.34	0.14	0.07	0.59
Task_tech_fit->Int_adop_mod2	0.11	0.12	0.13	-0.22	0.34
Perc_usef -> Int_adop_mod2	0.25	0.25	0.14	-0.15	0.46

$total.efs

Construct items	Original	Mean. Boot	Std. Error	perc. 025	perc .975
Task_char ->Tech_char	0	0	0	0	0
Task_char ->Task_tech_fit	0.397	0.414	0.108	0.221	0.618
Task_char ->Perc_usef	0.396	0.418	0.112	0.206	0.626
Task_char ->Perc_eas2	0.410	0.438	0.095	0.237	0.615
Task_char ->Int_adop_mod2	0.142	0.153	0.084	-0.060	0.279
Tech_char ->Task_tech_fit	0.321	0.255	0.244	-0.445	0.489
Tech_char ->Perc_usef	0.210	0.168	0.205	-0.403	0.406

Construct items	Original	Mean. Boot	Std. Error	perc. 025	perc .975
Tech_char ->Perc_eas2	0.116	0.084	0.104	-0.209	0.243
Tech_char ->Int_adop_mod2	0.088	0.068	0.093	-0.188	0.200
Task_tech_fit ->Perc_usef	0.449	0.403	0.166	0.081	0.662
Task_tech_fit ->Perc_eas2	0.362	0.340	0.142	0.070	0.586
Task_tech_fit->Int_adop_mod2	0.221	0.220	0.125	-0.180	0.412
Perc_usef -> Perc_eas2	0.000	0.000	0.000	0.000	0.000
Perc_usef -> Int_adop_mod2	0.252	0.247	0.142	-0.155	0.459
Perc_eas2 -> Int_adop_mod2	0.000	0.000	0.000	0.000	0.000

Table 7.
Inner model path coefficients table results in Inner Model $Task_tech_fit.

Construct items	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	5.76E-17	0.077	7.49E-16	1.00E+00
Task_char	4.08E-01	0.0796	5.13E+00	1.22E-06
Tech_char	3.08E-01	0.0796	3.87E+00	1.84E-04
$Perc_usef				
Construct items	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	7.29E-18	0.076	9.59E-17	1.00E+00
Task_tech_fit	5.80E-01	0.076	7.64E+00	7.11E-12
$Perc_eas				
Construct items	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	4.88E-17	0.0812	6.01E-16	1.00E+00
Task_tech_fit	4.91E-01	0.0812	6.05E+00	1.88E-08
$Int_adop_mod				
Construct items	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	1.45E-16	0.0884	1.64E-15	1
Perc_usef	3.68E-01	0.1011	3.64E+00	0.000413
Perc_eas	-1.04e-01	0.1011	-1.03E+00	0.304112

Model B: Modified model: Inner Model

$Task_tech_fit	Estimate	Std. error	t value	Pr(>|t|)
Intercept	5.90E-17	0.0777	7.60E-16	1.00E+00
Task_char	4.03E-01	0.0803	5.02E+00	1.93E-06
Tech_char	2.98E-01	0.0803	3.71E+00	3.25E-04
$Perc_usef	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-4.88E-17	0.0742	-6.58E-16	1.00E+00
Task_char	2.21E-01	0.0848	2.61E+00	1.04E-02
Tech_char	3.07E-02	0.0813	3.78E-01	7.06E-01
Task_tech_fit	4.63E-01	0.0895	5.17E+00	1.01E-06
$Perc_eas	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-9.64E-17	0.079	-1.22E-15	1
Task_char	2.68E-01	0.0903	2.97E+00	0.003688
Tech_char	-3.17E-02	0.0865	-3.67E-01	0.714348
Task_tech_fit	3.74E-01	0.0953	3.93E+00	0.000148
$Int_adop_mod	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	2.07E-16	0.0881	2.35E-15	1
Task_tech_fit	1.55E-01	0.1132	1.37E+00	0.173
Perc_usef	3.00E-01	0.1127	2.66E+00	0.009
Perc_eas	-1.55E-01	0.1052	-1.47E+00	0.143

The technology acceptance model was made up of Perceived Usefulness, Perceived ease of use, and Intention to adopt latent variables. Task-technology fit was made up of Task Technology Fit, Task Characteristics, and Technology characteristics.

To test each hypothesis, the inner model (structural model) results were mainly used see Table 7 (see. The results based on the coefficient sign assessed and p-value (if less than 0.05) were considered significant at a 5% level.

H1: Technology Acceptance Model predicts intention to adopt the design model.

H5: Perceived usefulness of the design model has an impact on intention to adopt the model.

H6: Perceived ease of use of the design model has an impact on intention to adopt the model.

In comparing path coefficients, perceived usefulness was the most accurate predictor of intention to adopt the design model. The coefficient value 0.368 (Table 6) showed a positive moderate relationship between perceived usefulness and intention to adopt. Nonetheless, there was a negative weak relationship (coefficient -0.104) between perceived ease of use and intention to adopt. Perceived ease of use had a weaker effect on university intentions to adopt the design model.

H2: Task characteristics of the design model were positively related to Task Technology Fit.

H3: Technology characteristics of the design model were positively related to Task Technology Fit.

Both Task characteristics and Technology characteristics had positive (0.408 and 0.308 respectively) coefficients. It was, therefore, concluded that there was a positive and strong relationship between task characteristics and task technology fit. In addition, there was a positive moderate relationship between technology characteristics and task-technology fit.

H4: Task technology fitness had an impact on the Technology Acceptance of the design model.

Task Technology fitness had a positive and significant effect on the Technology acceptance model (mainly Perceived usefulness and Ease of Use) since the coefficients were positive. The coefficients were 0.58 and 0.491 respectively.

H1: Technology Acceptance Model predicts intention to adopt the design model.

In the modified model, only Perceived Usefulness had a positive (0.30) and a significant effect on the intention to adopt. Task Tech fit which had been added (modified has a positive but insignificant effect on the intention to adopt) and Perceived Ease of use, harmed intention to adopt.

H2: Task characteristics of the design model are positively related to Task Technology Fit.

H_3: Characteristics of the design model are positively related to Task Technology Fit.

Both task characteristics and technology characteristics had a positive and significant effect on Task technology fit.

H_4: Task technology fitness had an impact on the Technology Acceptance of the design model.

Task Technology fit had a positive and significant effect on the Technology acceptance model (both Perceived usefulness and Perceived Ease of use) since both coefficients were positive (0.4634 and 0.374 respectively). However, it did not have a significant effect on Intention to adopt in the modified model framework.

5. Discussions

Based on the results presented the researchers accept H1: TAM predicts intention to adopt the model. H2 and H3 were also accepted; that is, task characteristics are positively related to task technology fit, and Technology characteristics are positively related to task technology fit. Ultimately, the researchers accepted H4: task technology fitness has an impact on TAM. Further to that, based on the analysis of the results, the researchers found statistical support to explain perceived usefulness and perceived ease of use on the intention to adopt the design model.

The study's results showed that task-characteristics and technology-characteristics (both task-technology fit constructs) had a significant effect on the technology acceptance model. This meant they were crucial for influencing technology adoption. These results were consistent with the initial hypothesis that task technology fitness had an impact on technology acceptance [30] employed the task-technology fit theory and suggests that technology drives users to engage in tasks and activities. As such, the inherent nature of technology was that, if it is not implemented technically, its utility to the Universities will not be there. The encouraging part, reflected in Wu and Chen [17], was that users of the integrated designs had experiences of working with other technologies, so they need not be trained to use new technology. Therefore, the perceived ease of use was a significant construct in explaining the adoption when compared to perceived usefulness.

Furthermore, perceived usefulness seemed to explain that the proposed integrated model could facilitate learning and reduce the lecturer's workload. Perceived ease of use did not seem to affect intention to adopt. This contradicted the original technology acceptance model [17]. The original model posits that information technology adoption is influenced by two perceptions: usefulness and ease-of-use. However, the findings in this study indicated that lecturers may not have the same perceptions.

6. Conclusion

In this study, the researchers combined design practice with theoretical software engineering principles. This facilitated requirements elicitation from students, lecturers, and software engineering experts. Stakeholders were engaged from the preliminary stages of the study, through to the evaluation of the proposed integrated designs. As a result, designing a model based on software engineering modelling provided a significant contribution to laying out the functionality of design components as they would relate to other components in the domain of educational digital technology systems. Further to that, focusing on the characteristics of software engineering artefacts was been of help in understanding the structure of e-learning management systems. Thus, the importance of this study lies in looking into the bigger picture of computer science education through design science research methods. The findings of this study offer practical contributions for developers and other stakeholders who engage in the design of technology-enabled teaching and learning tools in general, and computer science education, specifically.

While this study paid attention to the reusability of learning content in universities, specifically on application and integration characteristics of learning management systems, such ideas are also beneficial to enable the higher education sector to increase the rate of newer technology-based learning environments [31]. Integrated information systems about the technology used in teaching and learning are significant for lecturers as well as content authors. Their views, described in this study, would create a foundation knowledge for innovations that are done at a larger scale as well as related research. The practical value for lecturers is the reduced time in authoring content and uploading the same on a learning management system. One learning management system has been used broadly in Zimbabwe universities. This technology has been designed, not to reduce lecturers' burdens but to help them integrate technology into teaching. Therefore, this study contributes toward enhanced higher education teaching and learning. The key findings of this study are beneficial for policymaking. Digital technology thinking would provide policymakers with an understanding of who should be involved in the design processes, what other learning management systems features are required to support teaching and learning, and how the varied technological components relate to each other. It is worthwhile to note how the concept of integration fits into e-learning management systems, which have become a part of life for digital natives.

The researchers summarize the findings as follows. When designing systems to be implemented in universities to assist teaching and learning, emphasis should be put on the support that the university would offer to lecturers and students to perform their tasks. When the university management is willing to take the risk of implementing integrated repositories, resource sharing is improved and access to learning content via lightweight devices is enhanced.

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