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Factors Affecting Adoption Intention of Productivity Software Applications Among Teachers: A Structural Equation Modeling Investigation

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ABSTRACT
Teachers play a central role in achieving the mission, vision, and goals of educational institutions. However, the multitude of responsibilities and obligations they must fulfill demands a high level of productivity. Consequently, productivity software is increasingly becoming a necessity for teachers to lessen their day-to-day work pressure and instead focus on offering quality education. Despite their popularity, the key antecedents and precursors affecting the intention to use productivity software have yet to be investigated. Therefore, the goal of this study was to determine what factors contribute to the adoption of productivity software by applying the theoretical lens of the Technology Acceptance Model (TAM). A total of 947 responses from basic and higher education teachers were analyzed using a structural equation modeling approach. Results show that the usefulness and ease of use of productivity software are key in predicting behavioral intention. It is also indirectly affected by external variables such as subjective norms, professional reputation, job relevance, and output quality through perceived usefulness as well as facilitating conditions and self-efficacy through perceived ease of use. Overall, the findings of this study support the applicability of the specific TAM version as well as its employment in the context of productivity software.

1. Introduction

Productivity refers to the calculation of output per unit of inputs. It is an economic concept that measures how inputs (e.g., capital and labor) are efficiently used to produce a given level of output (e.g., goods and services). Improving productivity, by increasing outputs with fixed inputs, is a key source of competitiveness, profitability, and economic growth (Amato et al., 2022; Surya et al., 2021). On a side note, producing the same level of output with decreased inputs refer to the economic concept of efficiency. This comparison between productivity (maximize outputs) and efficiency (minimize inputs) is emphasized by Marginson (1991). In an educational context, the term productivity holds the same meaning, expressing the relationship between input and output (Hanushek & Ettema, 2017). However, Ladd and Hansen (1999) argued that educational productivity is more complex and elusive because there is a multiplicity of process and outcome objectives. For instance, input measures may include attendance records, instructional quality, and class size while output measures may include graduation, assessment scores, and employment. Nonetheless, researchers have been at the forefront of investigating how the education sector can achieve the best possible academic outcomes for the lowest possible cost (e.g., Aparicio et al., 2022; Fu & See, 2022; Rietveld et al., 2021).

Towards the realization of overarching educational goals and objectives, teachers play a significant role because of their lifelong impact on all their students. This is supported by OECD (2005) which posited school factors closer to the actual learning process as the strongest influence on educational effectiveness. More often, teachers are held accountable for the failure or success of institutions because their individual productivity reflects the productivity of the whole system (Etomes & Molua, 2018). When teachers are productive, they perform their work responsibilities (e.g., preparing lessons, researching new methods, and educating students) effectively, thereby contributing to the quality and overall school development. This ideal scenario led many researchers to probe how teachers can be productive, for instance, in terms of instructional capability (Bartkowiak et al., 2022), research outputs (Cardona, 2020), and work productivity (Utami & Vioreza, 2021). Despite the availability of these studies, there are still factors causing teachers to display low productivity (Anisah & Rusdinal, 2020; Mirali, 2021), ranging from individual issues (e.g., motivation, salary, and skills) to organizational culture (e.g., leadership, environment, and other external factors). With the expanding presence of technology in education, many studies positioned productivity software as a necessity in managing daily work responsibilities and encouraging a high level of productivity (e.g., Coulter, 2003). In this study, productivity

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software is any application software designed to simplify tasks and streamline workflow processes. Common examples of productivity software used by teachers include word processors, cloud storage, video conferencing software, online calendar, and more.

Following the idea of productivity improvement to accomplish more in less time as a result of working smarter and not harder (Marginson, 1991), this study deliberately adopted a narrower focus on productivity software. This is not to say that productivity software is certainly the only or best solution to improve productivity. Rather, unlike other solutions like salary (Britton & Propper, 2016) and training (Khan & Abdullah, 2019), the literature lacks a comprehensive understanding of how we can maximize technology for productivity improvement. While factors affecting the productivity of teachers have been examined repeatedly, the key antecedents and precursors determining the intention to use productivity software have yet to be investigated. Therefore, the goal of this study was to determine what factors contribute to the adoption of productivity software by applying the theoretical lenses of the Technology Acceptance Model (TAM; Davis, 1989) and its third version (TAM3; Venkatesh & Bala, 2008). With schools allocating budgets for technological investments (e.g., annual license subscriptions and software purchases), this study is significant for educational leaders and policymakers because it offers insights into how we can maximize and encourage the use of productivity software among teachers. The reliance on teacher productivity of student achievement and school effectiveness further strengthens the contribution of this study.

2. Theoretical framework

Since its first appearance more than 30 years ago (Davis, 1989), TAM has been unceasingly studied, criticized, expanded, and employed by numerous scholars to further our understanding of technology adoption. The consistent publication of TAM-related studies within various research disciplines not only boasts its popularity but also proves its vital role in understanding the predictors and determinants influencing human behavior towards a potential rejection or acceptance of technology. There are also other adoption theories (Taherdoost, 2018) but TAM is one of the most established technology acceptance models. In addition, a systematic literature review found that TAM is a credible model for facilitating the assessment of diverse technologies (Granić & Marangunić, 2019). Of the 73 eligible studies analyzed, almost half employed the original TAM while the other half extended the model by adding multifaceted constructs. These modifications are also often accomplished by using other theories, as indicated in another systematic review (Mustafa & Garcia, 2021). For instance, Prasetyo et al. (2021) combined TAM with the DeLone and McLean Model of Information Systems to investigate the factors that influence the adoption of online learning during the pandemic.

In the realm of educational research, the literature is rich when it comes to the adoption of various technology among teachers using TAM. For instance, Dele-Ajayi et al. (2019) investigated teachers' intention to use digital games in the classroom following the growing intersection of gaming and learning (e.g., Abdul Jabbar & Felicia, 2015; Garcia, 2020b; Wang et al., 2022). Another example is the study conducted by Mayer and Girwidz (2019), which investigated the acceptance of multimedia applications among physics teachers. Both studies aim to prepare students for life in a digital world by using the latest technologies as pedagogical tools. Ibili et al. (2019) likewise supported this goal by examining the level of acceptance and intention to use an augmented reality application among mathematics teachers. Student interest, engagement, immersion, and interactivity are some of the promises of this technology (Garcia, 2020a; Mazzuco et al., 2022; Theodoropoulos & Lepouras, 2021). On the other hand, Zafiropoulos et al. (2012) applied TAM to describe the behavioral intention of teachers to adopt e-government services. One common denominator among these studies is that they extended the TAM and incorporated various constructs to support their hypotheses.

Despite various extensions to TAM to accommodate the educational setting (e.g., Mustafa & Garcia, 2021), *Perceived Usefulness* (PU) and *Perceived Ease of Use* (PEOU) remained the most effective TAM constructs that determine individuals' intention to use technology. Accordingly, when technology enhances serviceability (i.e., PU) and is easy to use (i.e., PEOU), individuals are more likely to use that technology (Dele-Ajayi et al., 2019; Garcia, 2017; Ibili et al., 2019). This is supported by a meta-analysis that found PU and PEOU as significant constructs in predicting the Behavioral Intention to Use (BITU) digital technology among teachers (Scherer et al., 2019). Furthermore, the relationship between PU and PEOU has been described in earlier studies. For instance, a study conducted by Hong et al. (2021) indicated that PEOU affects PU, resulting in increased BITU. Contextualizing this finding to the present study, it is the assumption that when teachers perceive using productivity software demands little effort, they would also perceive them as useful. Therefore, this study proposes the following hypotheses:

H1. PU positively affects the BITU of productivity software among teachers.

H2. PEOU positively affects the BITU of productivity software among teachers.

H3. PEOU positively affects PU in the context of productivity software.

In TAM3, Venkatesh and Bala (2008) theorized the general determinants of PU using the constructs of *Subjective Norm* (SUBN), *Professional Reputation* (REPU; originally referred to as *Image*), *Job Relevance* (JOBR), *Output Quality* (OUTQ), and *Result Demonstrability* (RESD). While SUBN and REPU fall into the category of social influence, the remaining constructs of JOBR, OUTQ, and RESD are system characteristics that capture the influence of cognitive instrumental processes on PU. Social processes and mechanisms persuade individuals to believe that when an important person or group of people would approve of using technology (i.e., SUBN) or doing so would enhance their profile within a social system (i.e., REPU), the technology is useful to them. For instance, teachers will perceive the productivity software useful if their immediate supervisors support the utilization of such technology or if their co-teachers believe that they have more prestige because of this behavior. These scenarios are supported by earlier studies that found SUBN and REPU as positive significant constructs of PU (e.g., Lavidas et al., 2022; Rüth et al., 2022; Ursavaş et al., 2019). Drawing on three different theoretical paradigms (i.e., behavioral decision, action identification, and work motivation theories), the PU of technology is also determined by whether it can provide relevant and accurate information promptly and in an understandable format. By doing so, individuals will perceive higher output quality (i.e., OUTQ), greater job relevance (i.e., JOBR), and better result demonstrability (i.e., RESD). This is likewise supported by earlier studies showing that teachers perceive JOBR, OUTQ, and RESD as significant constructs of PU (e.g., Mayer & Girwidz, 2019; Zafiropoulos et al., 2012; Zhu & Zhang, 2022). Based on this discussion, this study also proposes the following hypotheses:

H4. SUBN plays a positively significant influence on the PU of productivity software.

H5. REPU plays a positively significant influence on the PU of productivity software.

H6. JOBR plays a positively significant influence on the PU of productivity software.

H7. OUTQ plays a positively significant influence on the PU of productivity software.

H8. RESD plays a positively significant influence on the PU of productivity software.

Building on the framing of human decision-making (*anchoring* and *adjustment*), Venkatesh and Bala (2008) also conjectured the general determinants of PEOU using the constructs of *Computer Self-Efficacy* (SELF), *Computer Playfulness* (PLAY), *Facilitating Conditions* (FCON), *Computer Anxiety* (CANX), and *Perceived Enjoyment* (PENJ). These constructs are a combination of general beliefs regarding computer use, control beliefs, intrinsic motivation, and system characteristics. Contextualizing the earlier empirical results in this study, we can assume that when teachers believe that they can perform a specific task using technology on their own (i.e., SELF) or if they are spontaneous when using them (i.e., PLAY), the PEOU construct becomes stronger (Chibisa et al., 2021; Rüth et al., 2022). Moreover, when there are an available support structure and organizational resources (i.e., FCON) permitting teachers to utilize technology easier, they are more likely to perceive that performing a task is simple and straightforward (Lavidas et al., 2022; Teo, 2009). On the contrary, when teachers are feeling anxious or fearful using technology (i.e., CANX), it disturbs the proper usage resulting in mistakes and making them intimidated and confused (Effiyanti & Sagala, 2018; Pittalis, 2021). Therefore, unlike other constructs, CANX negatively affects the PEOU construct. On the other side of the spectrum, when teachers enjoy performing an activity (i.e., PENJ) using technology without any reason other than doing it per se (intrinsic motivation), the PEOU is positively influenced (Teo & Noyes, 2011). Following these findings, this study finally proposes the remaining hypotheses:

H9. SELF positively affects PEOU in the context of productivity software.

H10. PLAY positively affects PEOU in the context of productivity software.

H11. FCON positively affects PEOU in the context of productivity software.

H12. CANX negatively affects PEOU in the context of productivity software.

H13. PENJ positively affects PEOU in the context of productivity software.

Given the empirical evidence surveyed, this study purposely selected and used TAM via its extended version as the theoretical foundation for investigating the adoption of productivity software among teachers. The proposed model with the corresponding hypothesized paths is presented in Figure 1, which is composed of 13 constructs defined in Table 1.

3. Materials and methods

This cross-sectional study employed a structural equation modeling (SEM) approach to construct a theoretical framework explaining the adoption of productivity software among teachers. SEM is a multivariate statistical framework that investigates complex relationships by measuring path coefficients for both direct and indirect effects (Anderson & Gerbing, 1988). This study followed the three-step approach used by Garcia (2017) in determining the adoption of learning management systems. First, an initial model was constructed based on the TAM and finalized the constructs using TAM3. The connections between these constructs were formed based on the literature review presented in the previous section. Then, the questionnaire consisted of 13 constructs (BITU, PU, PEOU, SUBJ, REPU, JOBR, OUTQ, RESD, SELF, PLAY, FCON, CANX, and PENJ; see Table 1) was developed to provide measures of the identified factors. A confirmatory factor analysis was also applied to assess the measurement model. Finally, following the guidelines suggested by Anderson and Gerbing (1988), the model was revised by individually modifying the constructs to avoid unnecessary effects. All procedures were conducted under the ethical principles of the institution and the Declaration of Helsinki.

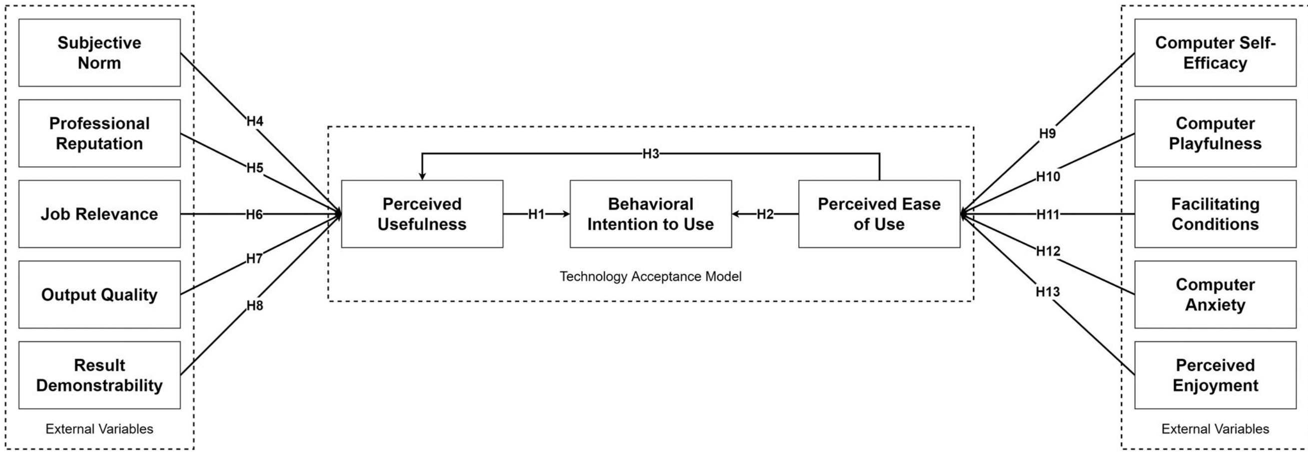

Figure 1. Proposed research model with hypothesized paths.

Table 1. Constructs and definition.

Constructs	Definition	Source
Behavioral Intention to Use	The degree to which teachers believe that they are going to use productivity software in the future	(Davis, 1989)
Perceived Usefulness	The degree to which teachers believe that using productivity software would enhance their performance	(Davis, 1989)
Perceived Ease of Use	The degree to which teachers believe that using productivity software would be free of effort	(Davis, 1989)
Subjective Norm	The degree to which teachers perceive that most people who are important to them would approve productivity software	(Fishbein & Ajzen, 1977)
Professional Reputation	The degree to which teachers perceive that using productivity software would enhance their social status	(Moore & Benbasat, 1991)
Job Relevance	The degree to which teachers consider that particular productivity software applies to their line of job	(Venkatesh & Davis, 2000)
Output Quality	The degree to which teachers believe that productivity software enhances the quality of their task outputs	(Venkatesh & Davis, 2000)
Result Demonstrability	The degree to which teachers believe that the results of using productivity software are tangible and communicable	(Moore & Benbasat, 1991)
Computer Self-Efficacy	The degree to which teachers believe that they can perform a specific task using productivity software	(Compeau & Higgins, 1995)
Computer Playfulness	The degree to which teachers may interact spontaneously with productivity software	(Hackbarth et al., 2003)
Facilitating Conditions	The degree to which teachers believe that technical and organizational resources exist to support productivity software	(Venkatesh et al., 2003)
Computer Anxiety	The degree to which teachers feel apprehension or fear when considering the implications of productivity software	(Cambre & Cook, 1985)
Perceived Enjoyment	The degree to which an activity using productivity software is perceived as enjoyable by teachers	(Teo & Noyes, 2011)

3.1. Measurement items

As presented in Table 1, all constructs were adopted from previous research studies as documented in TAM3 (Venkatesh & Bala, 2008). In addition to the definition of each construct, we also contextualized the instrument to reflect the context of productivity software. Using a judgment approach, the initial questionnaire was scrutinized in terms of completeness, format, and readability by researchers and teachers. The feedback from this preliminary analysis resulted in relatively small changes either by adding new or simplifying existing statements. Then, a pilot test was conducted on a convenience sample of teachers to assess the validity and reliability of the items in the revised questionnaire. All constructs have a Cronbach's alpha coefficient greater than 0.70, indicating an internally consistent questionnaire. The final validated questionnaire contained two main sections: (1) demographic information and (2) construct measurement (See Appendix A). The first section collected basic information about respondent characteristics, including age, gender, teaching experience, highest educational attainment, academic rank, and more. The second section is composed of 50 items to measure 13 constructs presented in the research model (Figure 1). All measurement items adopted a 5-point Likert scale, with answer options ranging from 1 (strongly disagree) to 5 (strongly agree).

3.2. Sample and data collection

The population for this study involved teachers who are presently working in any educational institution in the Philippines during the time of data collection. The non-probability sampling techniques of convenience and chain referral were used for participant recruitment. According to (Memon et al., 2017), a non-probability sample is still

Table 2. Demographic characteristics.

Characteristics	n	%
Gender		
Male	403	42.56
Female	544	57.44
Age		
18–24	36	3.80
25–34	358	37.80
35–44	295	31.15
45–54	201	21.22
55–64	57	6.02
65 and over	0	0.00
Teaching Experience		
Less than 3 years	42	4.44
3–5	102	10.77
6–10	276	29.14
11–15	189	19.96
16–20	132	13.94
21 and above	206	21.75
Marital Status		
Single	342	36.11
Married	565	59.66
Divorced	6	0.63
Separated	0	0.00
Widowed	34	3.59
Academic Rank		
Basic Education—Teacher	192	20.27
Basic Education—Master Teacher	48	5.07
Basic Education—Head Teacher	24	2.53
Higher Education—Lecturer/Instructor	342	36.11
Higher Education—Assistant Professor	172	18.16
Higher Education—Associate Professor	130	13.73
Higher Education—Professor	39	4.12
Work Schedule		
Part-Time	60	6.34
Full-Time	887	93.66
Employment Status		
Permanent	869	91.76
Non-Permanent	78	8.24
Type of Institution		
Public	828	87.43
Private	119	12.57
Highest Educational Attainment		
Bachelor	156	16.47
Master	477	50.37
Doctorate	314	33.16
Licensed Professional Teacher		
Yes	734	77.51
No	213	22.49

acceptable when the purpose is to test the proposed theoretical assumptions. The online self-administered questionnaire was distributed using Google forms between June 1 and 30, 2022 to various educational institutions in the country. To maximize the survey response rate, colleagues were contacted to request the forwarding of the questionnaire to their respective institutions and professional networks. A total of 947 responses were gathered (see Table 2), all of which were complete and usable for analysis. Most teachers are female ($n = 544$, 57.44%), married ($n = 565$, 59.66%), with an age ranging from 25 to 34 years ($n = 358$, 37.80%, mean = 38.61, standard deviation = 9.12) and a teaching experience ranging from 6 to 10 years ($n = 276$, 29.14%, mean = 14.02, standard deviation = 8.77). They work full-time ($n = 887$, 93.66%) as a permanent employee ($n = 869$, 91.76%) with a rank of lecturer/instructor ($n = 342$, 36.11%) in a public ($n = 828$, 87.43%) higher educational institutions ($n = 683$, 72.12%). Most of them are licensed professional teachers ($n = 734$, 77.51%) with a master's degree ($n = 477$, 50.37%). This demographic is consistent with a previous study that recruited Filipino teachers as study participants (Garcia & Oducado, 2021). Finally, in line with the goal to gather a representative sample of teachers in the country, this study collected data from the three geographical areas of the country although most responses came from Luzon (i.e., the largest and most populated island; $n = 600$, 63.36%).

3.3. Data analysis

Descriptive statistics and SEM were analyzed and performed using IBM SPSS Statistics 22 and IBM SPSS Amos 22, respectively. For SEM, a three-step approach was followed in testing research hypotheses similar to the technique employed by Okumus et al. (2016). First, the model was tested to assess the relationships between measurement items and latent variables. A confirmatory factor analysis was applied to assess the capability of the measurement model. Then, the SEM analysis was performed to calculate the standardization coefficient and correlation coefficient for every factor. The structural model was measured by evaluating its goodness-of-fit based on the values recommended by Schermelleh-Engel et al. (2003). As shown in Table 3, the measures were Chi-square/Degree of Freedom ($\chi2/df$), Goodness of Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Normed Fit Index (NFI), Non-Normed Fit Index (NNFI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA).

4. Results

Table 4 shows the results of the measurement model. The reliability was tested through composite reliability (CR) and results show that constructs ranged from 0.802 to 0.896, all exceeding the suggested 0.7 thresholds and thereby indicating an internally consistent questionnaire. In addition, the common method bias was examined using Harman's one-factor test. It was found that there is no risk of bias since the total variance extracted by a single factor does not exceed the 50% threshold (Podsakoff et al., 2003). On the other hand, the convergent validity was measured by assessing the average variance extracted (AVE). The AVE values ranged from 0.503 to 0.741 (AVE > 0.50) and are all greater than both the average shared variance (ASV) and maximum shared variance (MSV), which indicates that convergent validity is not a concern. For the discriminant validity, this study followed the suggestion of Fornell and Larcker (1981) to compare AVE with the squared correlation between constructs. As shown in Table 5, the squared correlations between pairs of constructs were all below the square root of AVE (i.e., the diagonal values in bold and italic), indicating compliance with the criterion. In addition to the Fornell and Larcker (1981) criterion, Henseler et al. (2015) recommended Heterotrait-Monotrait ratio of correlations (HTMT) as a criterion for detecting discriminant validity problems. Although HTMT is often applied to partial least squares SEM, it can also be used for covariance-based SEM (Rosli & Saleh, 2022). Discriminant validity problems occur when HTMT values are higher than the recommended threshold

Table 3. Goodness-of-fit measures of the research model.

Goodness-of-fit measures	good fit	Acceptable fit	Model value
Chi-square/Degree of Freedom (χ^2/df)	$0 \leq \chi^2 / df \leq 2$	$2 < \chi^2 / df \leq 3$	1.954
Goodness of Fit Index (GFI)	.95 ≤ GFI ≤ 1.00	.90 ≤ GFI < .95	0.921
Adjusted Goodness-of-Fit Index (AGFI)	.90 ≤ AGFI ≤ 1.00	.85 ≤ AGFI <.90	0.866
Normed Fit Index (NFI)	.95 ≤ NFI ≤ 1.00	.90 ≤ NFI < .95	0.911
Non-Normed Fit Index (NNFI)	.97 ≤ NNFI ≤ 1.00	.95 ≤ NNFI < .97	0.952
Comparative Fit Index (CFI)	.97 ≤ CFI ≤ 1.00	.95 ≤ CFI < .97	0.955
Root Mean Square Error of Approximation (RMSEA)	0 ≤ RMSEA ≤ .05	.05 < RMSEA ≤ .08	0.061

Note. The recommended values are derived from the study of Schermelleh-Engel et al. (2003).

Table 4. Measurement model results.

Constructs	Construct reliability	Average variance extracted	Average shared variance	Maximum shared variance
Behavioral Intention to Use (BITU)	.896	.741	.163	.221
Perceived Usefulness (PU)	.881	.649	.213	.338
Perceived Ease of Use (PEOU)	.874	.634	.246	.432
Subjective Norm (SUBJ)	.802	.503	.020	.063
Professional Reputation (REPU)	.830	.550	.290	.432
Job Relevance (JOBR)	.817	.598	.298	.432
Output Quality (OUTQ)	.851	.588	.213	.338
Result Demonstrability (RESD)	.819	.531	.165	.394
Computer Self-Efficacy (SELF)	.859	.670	.208	.490
Computer Playfulness (PLAY)	.852	.590	.164	.321
Facilitating Conditions (FCON)	.837	.631	.168	.368
Computer Anxiety (CANX)	.863	.558	.165	.394
Perceived Enjoyment (PENJ)	.860	.551	.282	.454

Table 5. Inter-construct correlations with square root of AVE

	BITU	PU	PEOU	SUBJ	REPU	JOBR	OUTQ	RESD	SELF	PLAY	FCON	CANX	PENJ
BITU	***0.861***												
PU	0.857	***0.806***											
PEOU	0.849	0.778	***0.796***										
SUBJ	0.785	0.756	0.357	***0.709***									
REPU	0.823	0.678	0.436	0.652	***0.742***								
JOBR	0.678	0.715	0.433	0.231	0.195	***0.773***							
OUTQ	0.752	0.727	0.526	0.125	0.453	0.651	***0.767***						
RESD	0.584	0.431	0.342	0.111	0.221	0.143	0.254	***0.729***					
SELF	0.809	0.345	0.732	0.243	0.478	0.215	0.541	0.260	***0.819***				
PLAY	0.725	0.511	0.785	0.153	0.234	0.183	0.111	0.157	0.235	***0.768***			
FCON	0.711	0.368	0.775	0.162	0.133	0.395	0.223	0.211	0.247	0.197	***0.794***		
CANX	−0.432	0.143	−0.311	0.243	0.414	0.215	−0.230	0.314	0.402	0.249	0.141	***0.747***	
PENJ	0.692	0.258	0.517	0.457	0.551	0.715	0.655	0.433	0.631	0.346	0.245	−0.265	***0.743***

Note. BITU: behavioral intention to use; PU: perceived usefulness; PEOU: perceived ease of use; SUBJ: subjective norm; REPU: professional reputation; JOBR: job relevance; OUTQ: output quality; RESD: result demonstrability; SELF: computer self-efficacy; PLAY: computer playfulness; FCON: facilitating conditions; CANX: computer anxiety; PENJ: perceived enjoyment; diagonal elements (bold and italic): Square root of AVE.

of 0.90. In this study, the HTMT values ranged from 0.038 to 0.839, which indicate that all constructs are independent of each other.

Table 6 presents the descriptive statistics using mean and standard deviation (M ± SD) including the results of the initial and final factor loading. Results show that most teachers intend to use the technology as the mean BITU score indicates an agreement (4.16 ± 1.024). Meanwhile, all constructs are significant predictors of teachers' adoption intention of productivity software ($p < 0.05$). The initial SEM model was presented on Figure 2. Items such as SUBJ1, RESD2, PLAY1, CANX4, and PENJ5 have values less than the 0.05 threshold. Therefore, a revised model was reconstructed by omitting non-significant latent indicators to strengthen the model's fit.

As there were several inter-construct correlations higher than the threshold value of 0.60 (see Table 5), a supplementary test was performed to address the possible multicollinearity issue. Specifically, the variance inflation factor (VIF) was analyzed as well as the tolerance values for each construct. We can verify the existence of multicollinearity when the VIF values are greater than 10, or if the tolerance values are less than 0.10. Multicollinearity is not an issue in this dataset because the highest VIF was 3.67 and the lowest tolerance value was 0.36.

Following the satisfactory findings concerning the measurement model, this study deployed SEM to test the research hypotheses. As mentioned, the goodness-of-fit measures were used to evaluate the overall structural model fit. The results of the analysis show that the fit between the dataset and the measurement model was satisfactory ($\chi^2/df = 1.95$; GFI = 0.90; AGFI = 0.86; NFI = 0.91; NNFI = 0. 95; CFI = 0.95; and RMSEA = 0.06) as presented on Table 3. All the fit indices for the final model indicated either an acceptable or good structural model fit.

Finally, Table 7 presents the summary of study results, which shows that 8 out of 13 hypotheses were supported. The total explain variance for BITU ($R^2 = 72.28\%$), PU ($R^2 = 70.16\%$), and PEOU ($R^2 = 66.32\%$) are all considered "high". These results match the findings from a prior study

Table 6. Descriptive statistics and factor loading.

Constructs	Variables	*M* ± *SD*	Factor loading	
			Initial	Final
Behavioral intention to use (BITU)	BITU1	4.16 ± 0.980	.869	.874
	BITU2	4.12 ± 0.983	.844	.841
	BITU3	4.19 ± 0.996	.882	.867
Perceived usefulness (PU)	PU1	4.42 ± 1.107	.813	.824
	PU2	4.38 ± 1.092	.813	.812
	PU3	4.40 ± 1.094	.829	.803
	PU4	4.44 ± 1.085	.758	.784
Perceived ease of use (PEOU)	PEOU1	4.08 ± 1.057	.826	815
	PEOU2	4.08 ± 1.087	.811	.807
	PEOU3	4.10 ± 1.117	.787	.767
	PEOU4	4.19 ± 1.135	.803	.796
Subjective norm (SUBJ)	SUBJ1	2.74 ± 1.813	.497	–
	SUBJ2	4.00 ± 1.047	.714	705
	SUBJ3	4.11 ± 1.087	.722	.723
	SUBJ4	3.99 ± 1.107	.735	.711
Professional reputation (REPU)	REPU1	4.36 ± 1.245	.788	.785
	REPU2	4.32 ± 1.104	.743	.737
	REPU3	4.42 ± 1.014	.715	.742
	REPU4	4.44 ± 1.046	.719	.722
Job relevance (JOBR)	JOBR1	4.40 ± 1.088	.763	.771
	JOBR2	4.38 ± 1.092	.791	.810
	JOBR3	4.41 ± 1.095	.766	.775
Output quality (OUTQ)	OUTQ1	4.19 ± 1.072	.763	.787
	OUTQ2	3.99 ± 1.161	.778	.788
	OUTQ3	4.14 ± 1.086	.771	.761
	OUTQ4	4.11 ± 1.112	.755	.736
Result demonstrability (RESD)	RESD1	4.08 ± 1.057	.697	.701
	RESD2	3.03 ± 1.552	.397	–
	RESD3	4.04 ± 1.056	.745	.734
	RESD4	4.01 ± 1.026	.719	.745
Computer self-efficacy (SELF)	SELF1	3.59 ± 1.133	.812	.785
	SELF2	3.27 ± 1.180	.825	.856
	SELF3	3.31 ± 1.192	.819	.821
Computer playfulness (PLAY)	PLAY1	3.16 ± 1.273	.467	–
	PLAY2	4.07 ± 1.084	.789	.781
	PLAY3	3.87 ± 1.072	.771	.768
	PLAY4	3.90 ± 1.079	.745	.765
Facilitating conditions (FCON)	FCON1	3.75 ± 1.117	.786	.743
	FCON2	3.85 ± 1.060	.784	.753
	FCON3	3.79 ± 1.090	.812	.823
Computer anxiety (CANX)	CANX1	2.51 ± 1.205	.711	.708
	CANX2	2.44 ± 1.165	.792	.791
	CANX3	2.41 ± 1.238	.724	.743
	CANX4	3.46 ± 1.225	.518	–
	CANX5	2.37 ± 1.432	.748	.755
Perceived enjoyment (PENJ)	PENJ1	3.57 ± 1.211	.744	.738
	PENJ2	3.56 ± 1.326	.741	.729
	PENJ3	3.76 ± 1.214	.752	.765
	PENJ4	3.65 ± 1.109	.764	.749
	PENJ5	2.46 ± 1.058	.431	–

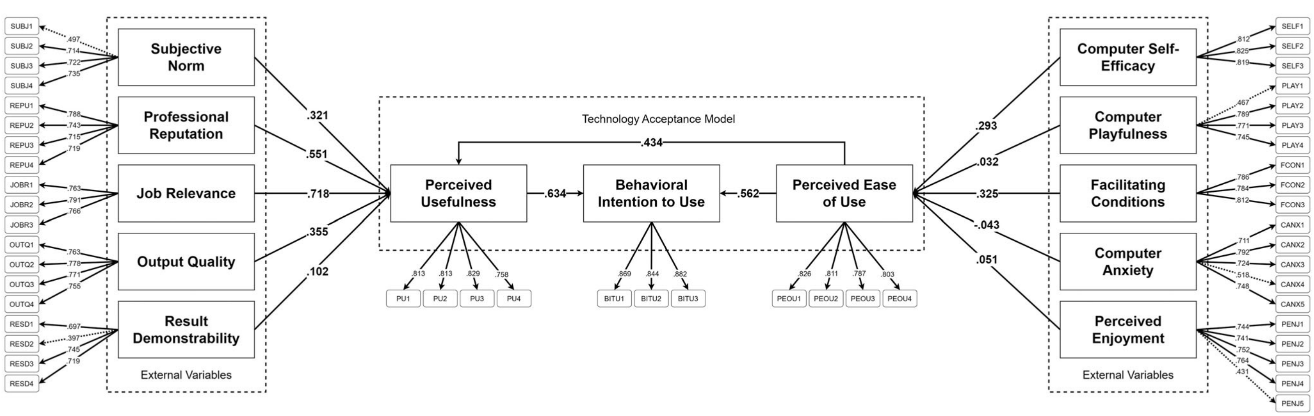

Figure 2. The initial SEM model for the adoption intention of productivity software applications among teachers.

on teachers' acceptance of technologies (e.g., Lavidas et al., 2022). Figure 3 presents the final model for evaluating the factors affecting teachers' adoption intention of productivity software applications.

5. Discussion

5.1. General findings

Productivity is an important measure that contributes to the quality and overall school development. Considering the barriers causing teachers to display low productivity, many studies positioned productivity software as a necessity in alleviating this situation. However, it is unclear whether teachers intend to use productivity software and what factors could influence their decision. This research gap prevents the development of a theoretical model that can explain how teachers decide whether to use productivity software. Without this understanding, educational institutions can only guess haphazardly whether to invest in a particular productivity software. To fill this gap, this study adopted an extended TAM to explain their technology acceptance level.

Table 7. Hypothesis testing results.

H#	Structural paths	Standardized Path Coefficients	*p*-Value	Result
H1	PU → (+) BITU	.634	.011	Supported
H2	PEOU → (+) BITU	.561	.002	Supported
H3	PEOU → (+) PU	.446	.016	Supported
H4	SUBJ → (+) PU	.334	.002	Supported
H5	REPU → (+) PU	.549	.010	Supported
H6	JOBR → (+) PU	.722	.000	Supported
H7	OUTQ → (+) PU	.373	.041	Supported
H8	RESD → (+) PU	.086	.055	Not Supported
H9	SELF → (+) PEOU	.308	.039	Supported
H10	PLAY → (+) PEOU	.024	.085	Not Supported
H11	FCON → (+) PEOU	.331	.033	Supported
H12	CANX → (−) PEOU	−.064	.068	Not Supported
H13	PENJ → (+) PEOU	.042	.071	Not Supported

Note. BITU: behavioral intention to use; PU: perceived usefulness; PEOU: perceived ease of use; SUBJ: subjective norm; REPU: professional reputation; JOBR: job relevance; OUTQ: output quality; RESD: result demonstrability; SELF: computer self-efficacy; PLAY: computer playfulness; FCON: facilitating conditions; CANX: computer anxiety; PENJ: perceived enjoyment.

Results show that most teachers intend to use productivity software as the mean BITU score indicates an agreement (4.16 ± 1.024). This level of usage intention implies that teachers appreciate the benefits of these technologies that enable them to be more productive in the workplace and at home. According to Coulter (2003), productivity software allows teachers to free up their time and redirect it to the instruction side of their jobs. One scenario is when they use *Microsoft Excel* which saves time when computing students' grades rather than doing it manually. Given the multitude of responsibilities and additional tasks given to teachers, having a technology that increases quality time on tasks and lessens the labor burden is superior to not having one. The same rationale is reflected in other academic community members and why they should maximize technology (e.g., librarians using a self-service library system; Garcia, 2019). Without the assistance of productivity software, teachers may have to extend their working hours and bring their incomplete tasks home. According to Austin et al. (2005), this excessive workload as well as the hours spent working outside schools are some of the major causes of work-related stress among teachers. Unfortunately, stress has also a negative impact on their productivity (Yusuf et al., 2015). In a complete snapshot, teachers can improve their productivity when they are provided with a support that can lessen their work-related stress. A trend is also becoming more apparent where teachers use productivity software inside the classroom. For instance, teachers can also use *Microsoft Excel* to demonstrate mathematical formulas as part of their teaching strategies. The expanding utility of productivity software, from clerical to educational tasks, makes them even more valuable for teachers. Technology can be expensive, but this finding warrants further consideration for governments and schools to invest in productivity software.

5.2. Perceived usefulness and perceived ease of use

As hypothesized in *H1* and *H2*, the BITU is positively affected by PU ($\beta = 0.634$, $p = 0.011$) and PEOU ($\beta = 0.561$, $p = 0.002$), respectively. These hypotheses are simply a confirmation in the context of productivity software since PU and PEOU are two of the strongest determinants of BITU

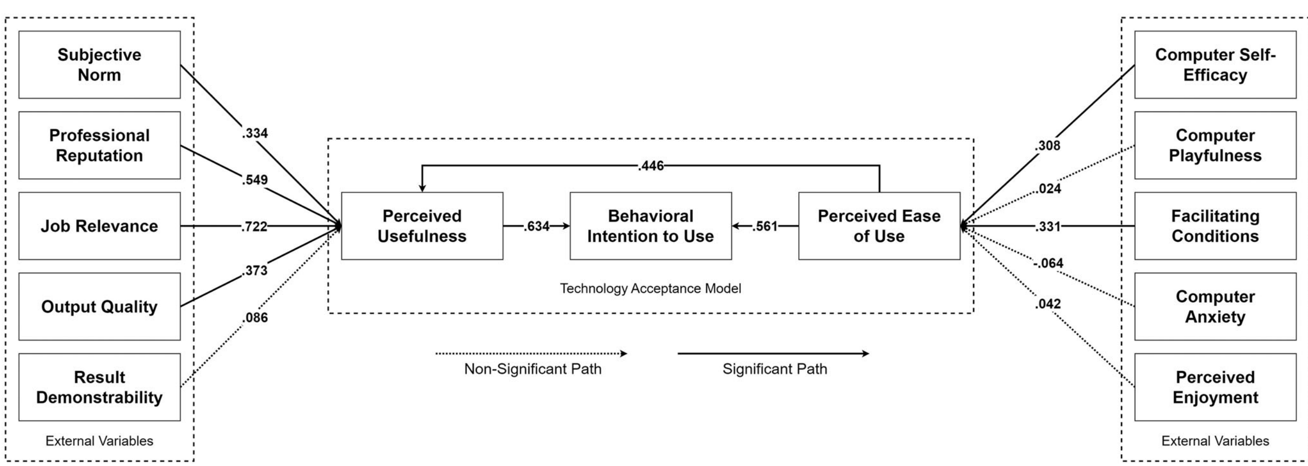

Figure 3. The final model for the adoption intention of productivity software applications among teachers.

(Garcia, 2017). It likewise confirms the systematic literature review of TAM in an educational context that emphasizes usefulness and ease of use perceived by users (e.g., teachers and learners) as antecedents of technology usage (Granić & Marangunić, 2019). In addition, PEOU positively influences PU ($\beta = 0.446$, $p = 0.016$) as hypothesized in *H3*, validating that the core TAM constructs are indeed significant. This finding is consistent with various TAM-based studies that investigated the acceptance and intention to use technologies among teachers (e.g., Dele-Ajayi et al., 2019; Garcia, 2017; Hong et al., 2021; Ibili et al., 2019; Scherer et al., 2019). Notably, PU has a greater total effect than PEOU on BITU, which contradicts Hong et al. (2021) but agrees with Lavidas et al. (2022). With consideration of the specific technology and participants of these studies, it is possible that when teachers are already familiar with the technology, they are more likely to prioritize PU than PEOU when adopting technology. This finding partially explains why JOBR was the strongest predictor among all constructs. In the case of this study, the participants may be already accustomed to and are using productivity software to keep their productivity high while working from home during emergency remote education (Garcia & Revano, 2022). This familiarity with how to use a technology implies that the ease of use of the productivity software is not as much of a concern as its usefulness.

5.3. External variables influencing perceived usefulness

Among the constructs hypothesized that could influence PU, only RESD (*H8*) was not significant. First, the positive bearing of social mechanisms through the constructs of SUBJ (*H4*; $\beta = 0.334$, $p = 0.002$) and REPU (*H5*; $\beta = 0.549$, $p = 0.010$) to PU emphasizes the importance of interaction between individuals and social environments, which is consistent with prior literature (e.g., Lavidas et al., 2022; Rüth et al., 2022; Ursavaş et al., 2019). This is unsurprising since social support has a direct and positive predictive power on the professional identity of teachers, and this professional identity influences their teaching efficacy (Li & Xie, 2022). From a managerial perspective, these results propose that a proper introduction to and a series of training on a particular productivity software is necessary. These actions will establish the educational value of these technologies among teachers within the same social system. Although it is not a construct in this study, teacher training experience likewise positively influences PU and PEOU (Mailizar et al., 2021). On the other hand, among the system characteristics that capture the influence of cognitive instrumental processes on PU, only JOBR (*H6*; $\beta = 0.722$, $p = 0.000$) and OUTQ (*H7*; $\beta = 0.373$, $p = 0.041$) were significant. This finding concurrently supports (JOBR) and contradicts (OUTQ) the adoption of e-government services by teachers (Zafiropoulos et al., 2012). One possible reason is that these services do not align with the needs of teachers and therefore are not considered useful. Following this notion, another managerial implication of this study is that educational leaders should select productivity software carefully to ensure teachers will use them and thereby can work effectively. Overall, emphasizing the advantages of these productivity software applications and their benefits to accomplishing academic tasks would lead to higher levels of PU, which subsequently would lead to higher levels of BITU.

5.4. External variables influencing perceived ease of use

Contrary to the literature review, only SELF (*H9*; $\beta = 0.308$, $p = 0.039$) and FCON (*H11*; $\beta = 0.331$, $p = 0.033$) significantly influences PEOU. The effect of SELF on PEOU is in agreement with previous research (e.g., Lavidas et al., 2022), which means that teachers who can easily perform tasks with productivity software are interested in continuing to use them. Aside from the training program proposed to establish the educational value of productivity software, this study also recommends that institutions should ascertain the availability of technical support services that could train or assist teachers for them to develop a strong sense of self-efficacy (Chibisa et al., 2021). Coincidentally, the availability of sustainable and relevant professional development sessions as well as the provision of technical support are under FCON, which is another significant construct that impacts PEOU and is in line with prior studies (e.g., Teo, 2009). According to Gomez et al. (2022), teachers' willingness to learn to use technology is key for successful integration. Others who resist change in their institutional practices may need a more extensive intervention or else the technology adoption level may suffer. Meanwhile, the diversion from the literature of PLAY (*H10*), CANX (*H12*), and PENJ (*H13*) may indicate a possible context specificity. For instance, the insignificant effect of PLAY and CANX exhibits the familiarity and confidence of teachers in productivity software. According to Hackbarth et al. (2003), when users first interact with technology, they are more apt to explore and interact spontaneously with it. In the context of productivity software, teachers are not experiencing anxiety because of their prior experience with them. Incorporating the social cognitive theory in TAM, McFarland and Hamilton (2006) found that prior experience significantly influences SELF and other TAM constructs.

5.5. Theoretical and managerial implications

From a theoretical standpoint, the present study contributes to the literature on technology adoption theories by testing an extended TAM. It serves as an indicator that reflects teachers' adoption intention level of productivity software applications. With schools investing heavily in their technological infrastructures (e.g., annual license subscriptions and software purchases), determining the antecedents of technology acceptance is an important phenomenon to explore. As one of the most used technologies in education, educational leaders and policymakers must understand how their teachers decide and what factors influence their intention to use productivity software. This knowledge is valuable to ensure efficient resource allocation, which is even more critical for underfunded schools. According to Bass (2021), school funding for technology resources affects school-level student proficiency. The findings of the present study also emphasize the importance of interaction between individuals and social environments through the SUBJ variable. This result informs educational leaders that a proper introduction to and a series of training on a particular productivity software is worthwhile to establish its educational value for teachers within the same social system. More importantly, Gomez et al. (2022) asserted that teachers must hone their technological skills since their willing disposition to learn a technology is key for successful integration. School managers must also identify teachers who may resist the expansion of their repertoire and implement an appropriate intervention to develop a strong sense of task-specific self-efficacy.

5.6. Limitations and future works

Unlike the vast majority of previous works that were limited to a single educational institution (Granić & Marangunić, 2019), the respondents from this study were from different public and private schools with representatives from basic and higher education institutions across the country. Nevertheless, this study has some limitations that could serve as future research avenues. First, its cross-sectional nature prevents the incorporation of the actual use of productivity software. Methodologically, a longitudinal research design is recommended to investigate any changes throughout one's teaching career as well as investigate the relationship between BITU and actual usage. Second, this study did not empirically test the relationships between the demographic profiles of the respondents and the extended TAM constructs (e.g., Garcia et al., 2022). Future studies may also consider other variables (e.g., attitude and usability) that have the potential to predict BITU and are of interest to the education community. It is also recommended to consider other models like UTAUT when replicating this study. Valuable insights can also emanate from further examining the unsupported hypotheses. Third, "productivity software" was used in a general sense regardless of purpose and design, and it is possible that the views of teachers vary depending on the specific technology. For instance, they may find *Microsoft Excel* more favorable if they use it in their grade computations compared to other productivity software. Finally, this study was limited to in-service teachers but could be replicated with pre-service teachers or other professionals. By doing so, educational leaders, policymakers, and teachers can devise strategies that foster positive behavior toward productivity software at the teacher training stage.

6. Conclusion

Teachers play a central role in achieving the mission, vision, and goals of any educational institution. However, the multitude of responsibilities and obligations they must fulfill demands a high level of productivity. Therefore, productivity software is increasingly becoming a necessity for teachers to lessen their day-to-day work pressure and rather focus on offering quality education. Building upon the lack of prior research, this study theoretically proposed and empirically validated an extended TAM in educational settings. Based on the SEM approach, a total of 947 responses from basic and higher education teachers were analyzed to examine the factors affecting their adoption of productivity software. The findings of this study support the applicability of the specific TAM version as well as its employment in the context of this subset of technology. According to teachers, the usefulness and ease of use of productivity software are key in predicting their intention to integrate this technology into their workflows. More importantly, it is also indirectly affected by external variables such as subjective norms, professional reputation, job relevance, and output quality through perceived usefulness as well as facilitating conditions and self-efficacy through perceived ease of use. Overall, this study contributes to both theory and practice of TAM in educational contexts.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A. Survey Questionnaire

SECTION 1: Demographic Information

What is your age? (years)

____

How long have you been teaching? (years)

____

What is your gender?
◯ Male
◯ Female

What is your highest educational attainment?
◯ Bachelor
◯ Masters
◯ Doctorate

What is your marital status?
◯ Single
◯ Married
◯ Divorced
◯ Separated
◯ Widowed

What is your academic rank?
◯ Basic Education – Teacher
◯ Basic Education – Master Teacher
◯ Basic Education – Head Teacher
◯ Higher Education – Lecturer/Instructor
◯ Higher Education – Assistant Professor
◯ Higher Education – Associate Professor
◯ Higher Education – Professor

Where is your school located?
◯ Luzon
◯ Visayas
◯ Mindanao

What is your work schedule?
◯ Full-time
◯ Part-time

In what school sector do you belong?
◯ Public
◯ Private

What is your employment status?
◯ Permanent
◯ Non-Permanent

Are you a licensed/registered professional teacher?
◯ Yes
◯ No

SECTION 2: Technology Acceptance Model

Behavioral Intention to Use

BITU1	Assuming I had access to a productivity tool, I intend to use it.
BITU2	Given that I had access to a productivity tool, I predict that I would use it.
BITU3	I plan to use productivity tools in the future.

Perceived Usefulness

PU1	Using productivity tools would enable me to accomplish tasks more quickly.
PU2	Using productivity tools would enhance my job performance.
PU3	Using productivity tools would make my job easier.
PU4	I would find productivity tools useful in my job.

Perceived Ease of Use

PEOU1	Learning to operate productivity tools would be easy for me.
PEOU2	I would find it easy to get productivity tools to do what I want them to do.
PEOU3	My interaction with productivity tools would be clear and understandable.
PEOU4	It would be easy for me to become skillful at using productivity tools.

Job Relevance

JOBR1	Productivity tools are relevant to my job as an educator.
JOBR2	Productivity tools are important to my job as an educator.
JOBR3	Productivity tools can help me with my tasks as an educator.

Subjective Norm

SUBJ1	Most people who are important to me think that I should use productivity tools.
SUBJ2	My co-teachers think that I should use productivity tools.
SUBJ3	My immediate supervisor thinks that I should use productivity tools.
SUBJ4	People around my workplace use productivity tools.

Professional Reputation

REPU1	Using productivity tools would enhance my prestige among my students.
REPU2	Using productivity tools would enhance my prestige among my co-teachers.
REPU3	Using productivity tools would enhance my prestige among my supervisors.
REPU4	Using productivity tools would enhance my prestige in the academic community.

Output Quality

OUTQ1	The quality of the output I get from productivity tools is high.
OUTQ2	I have no problem with the quality of productivity tools.
OUTQ3	I rate the results from productivity tools to be excellent.

Result Demonstrability

RESD1	I think I can communicate to others the consequences of using productivity tools.
RESD2	I have no difficulty telling others about the results of using productivity tools.
RESD3	The results of using productivity tools are apparent to me.

Computer Self-Efficacy

SELF1	I can use productivity tools even if there is no one around to show me how to do it.
SELF2	I can use productivity tools even if I have never used such a system before.
SELF3	I can use productivity tools even if I have only the software manuals for reference.

Computer Playfulness

PLAY1	I am unimaginative when using productivity tools.
PLAY2	I am creative when using productivity tools.
PLAY3	I am playful when using productivity tools.
PLAY4	I am spontaneous when using productivity tools.

Computer Anxiety

CANX1	Productivity tools make me feel uneasy.
CANX2	Productivity tools make me feel uncomfortable.
CANX3	Working with productivity tools makes me nervous.
CANX4	I get a sinking feeling when I think of trying to use productivity tools.

Facilitating Conditions

FCON1	I have the resources necessary to use productivity tools.
FCON2	I have the knowledge necessary to use productivity tools.
FCON3	Technical support is available for assistance with productivity tools.

Perceived Enjoyment

PENJ1	I find using productivity tools generally enjoyable.
PENJ2	The actual process of using productivity tools is pleasant.
PENJ3	I do not realize the time elapsed when I use productivity tools.
PENJ4	I have fun using productivity tools.
PENJ5	I enjoy using different features of productivity tools.