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Determining the Factors Affecting a Career Shifter's Use of Software Testing Tools amidst the COVID-19 Crisis in the Philippines: TTF-TAM Approach

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Abstract: The restrictions of the ongoing COVID-19 pandemic resulted in the downturn of various industries and in contrast a massive growth of the information technology industry. Consequently, more Filipinos are considering career changes to earn a living. However, more people still need to be upskilled. This study combines the extended Technology Acceptance Model and Task Technology Fit framework to determine factors affecting a career shifter's use of software testing tools and its impact on perceived performance impact amidst the COVID-19 pandemic in the Philippines. A total of 150 software testers voluntarily participated and accomplished an online questionnaire consisting of 39 questions. The Structural Equation Modeling and Deep Learning Neural Network indicated that Task Technology Fit had a higher effect on Perceived Performance Impact. Moreover, Task Technology Fit positively influenced Perceived Usefulness. Computer Self-Efficacy was a strong predictor of Perceived Ease of Use. Perceived Ease of Use confirmed the Technology Acceptance Model framework as a strong predictor of Actual System Use. Intention to Use, Perceived Usefulness, Actual Use, and Subjective Norm were also significant factors affecting Perceived Performance Impact. This study is the first to explore the career shifter's use of software testing tools in the Philippines. The framework would be very valuable in enhancing government policies for workforce upskilling, improving the private sector's training and development practices, and developing a more competitive software testing tool that would hasten users' adaptability. Lastly, the methodology, findings, and framework could be applied and extended to evaluate other technology adoption worldwide.

Keywords: structural equation modeling; deep neural network; task technology fit; career shifter; software testing tools

1. Introduction

Shifting careers into the technology sector has gained interest since the COVID-19 pandemic has begun [1,2]. Despite the downturn of various industries during the pandemic, the global information technology (IT) industry experienced rapid growth [3,4]. As more businesses shift to technological solutions [3], shifting careers to the software development and IT industry has become a viable option for many [4–9]. In the Philippines, most technology-related profession focuses more on the usage of technology testing. These professions circle around jobs in computer programming, system analysis, web design and development, IT support, information security analysis, and data science [10].

The increase in the utilization of technology and testing technology jobs in several industries has been evident [9–14]. However, the rapid change led to the need to fill the skills gap in order to meet demands [4,5,11]. It was seen that technology-related industries are able to provide higher salaries and sustainable jobs, and have relatively high demands, especially in the Philippines. Thus, the increase in career shifts, especially in the technology-related field, has been evident. Career shifters must be able to adapt and use these technologies to upskill and perform well in their respective organizations. Thus, previous studies have utilized technology acceptance theories to study user acceptance and adoption of new technology [15–17].

Several models such as the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) model have been widely utilized. TAM is a framework that considered the perceived usefulness and perceived ease of use among respondents, which affects their attitude, intention to use the technology, and eventually the actual use of a system [18]. Hancerliogullari Koksalmis and Damar [18] explained how common TAM does not consider attitude anymore, especially when perception in usefulness and ease of use are present. In their study, it was seen how utilizing TAM was able to analyze SAP ERP systems adoption. The study of Shamsi et al. [19] considered the use of TAM integrated with job-demand resources theory to analyze work-related well-being during the COVID-19 pandemic. Their results showed how the application of integrated theories would holistically measure the target object. In their case, the mental workload, perceived ease of use, and perceived usefulness impacted the engagement and usage of technology among users. However, TAM focuses solely on the evaluation of behavioral intentions and does not consider other factors such as interpersonal influences as seen in Figure 1. Several studies have incorporated the integration of TAM with TTF.

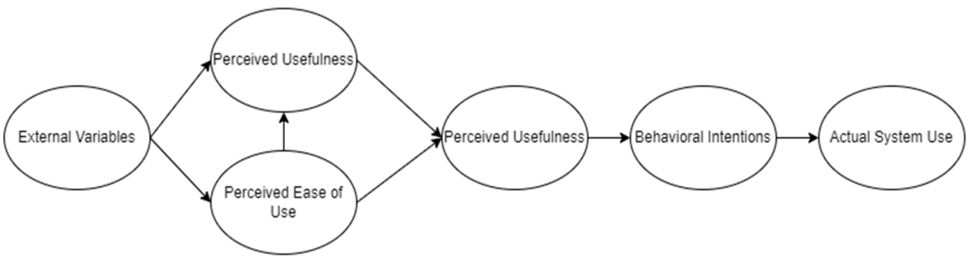

Figure 1. Technology Acceptance Model (TAM).

The Task Technology Fit model has been utilized widely in the professional sector. The study of Wu and Tian [20] considered the TTF model with the evaluation of enterprise social networks. They found that TTF alone was not sufficient to completely measure other aspects of social networks as seen in Figure 2. For the applicability of their study, they utilized the DeLone and IS Success Model. The results presented TTF variables and perception of usage among users influenced their continuous usage. Similarly, the study of Wu et al. [21] considered the integration of TTF, the initial trust model, and the extended unified theory of acceptance and use of technology in assessing the usage of cross-border mobile payments. They utilized three models to consider all areas of trust, behavior, and new technology adoption. In line with this, the study of Chuenyindee et al. [22] criticized TAM alone and TTF alone to be insufficient when it comes to evaluating technology-related adoption, user behavior, and actual use. Thus, their study considered integrating TAM, TTF, and the system usability scale to holistically measure learning management systems during online learning in the COVID-19 pandemic era. Their result presented that TAM and TTF integration would suffice in measuring new technology usage and adoption among users. However, their study only considered only the technology characteristics and TTF latent variables as deemed necessary. It could therefore be deduced that latent variables in this model are flexible depending on the applicability of the technology being evaluated. Thus, several related studies on the usage of technology in the industry and education sector have integrated both theories to completely measure aspects of technology adoption and usage.

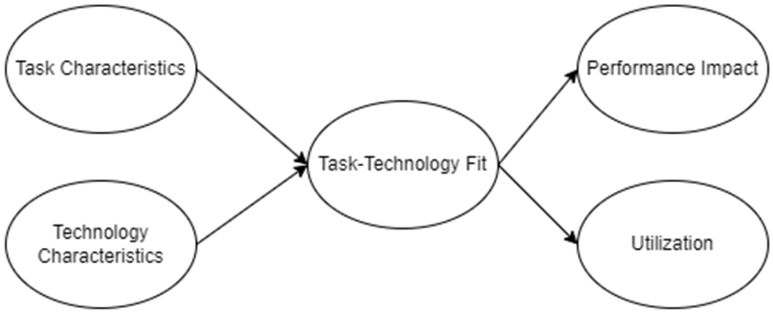

Figure 2. Task Technology Fit Model (TTF).

The study of Sun et al. [23] integrated the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) to evaluate factors affecting the intention to use and actual use of Enterprise Resource Planning (ERP) systems. Moreover, how these factors affect individual performance was also analyzed. The implications suggested that TTF is a more crucial indicator than actual IT use in realizing the performance impacts on organizations [23]. The TAM–TTF framework was integrated with Delone and McLean's IS model in the study of the adoption of a procurement system in Indonesia [24]. The results showed that a good fit between task and technology, usage experience, and user satisfaction impact individual performance [24]. A similar TAM, TTF, and IS model was used in the analysis of the use of e-budgeting software in the Ministry of Public Works and Housing in Indonesia [25]. In their study, TTF influenced perceived usefulness and perceived ease of use, and these two factors affect the intention and actual use of the software [25]. The use of software measures was the focus of the study of Wallace and Sheetz with TAM as their framework [26]. They have implied that understanding adaptability enables the development of software that is perceived as useful and easy to use [26]. In addition, the study of Yen et al. [27] presented how TAM is used to measure user acceptance while TTF is used to measure technology fit for a certain task. In their study assessing factors affecting user acceptance of a new wireless technology, they integrated both TAM and TTF which holistically measure behavioral and interpersonal variables. On the other hand, the study of Wu et al. [28] considered both models to measure MOOC continuance intention and usage. Their study justified the usage of integrated models for comprehensive measurement and understanding of behavioral intentions and actual use of technology. Lastly, their study also presented how the development of technology and software needs evaluation, especially for newly established systems.

Development of software includes testing to ensure quality [29–31]. Quality assurance activities such as software testing are performed through the use of software testing tools such as HP ALM, Selenium, and JMeter [32]. As the software testing market increases at a 7% Compound Annual Growth Rate (CAGR) globally, the scarcity of software testers grows [33]. In spite of the high demand, a developing country such as the Philippines is faced with a shortage of critical technical skills and competencies [34,35]. As a response, the government has already been pushing for the passage of "the Philippine Digital Workforce Competitiveness Act" Senate Bill 1834 to equip Filipinos with 21st century digital skills [36]. However, there is still a scarcity of studies in the Philippines that focus on the adoption and use of technology in workplace settings.

The need to assess the adoption and usage of software testing tools should be addressed since this newly applied technology in the Philippines is gaining attention. The assessment of this type of technology would lead to more sustainable development for continuous usage. This study aimed to determine the factors affecting a career shifter's use of software testing tools towards the perceived performance impact amidst the COVID-19 crisis in the Philippines by using the combined TTF and extended TAM framework. This research is the first to explore the adoption and use of software testing tools among career shifters in the Philippines utilizing structural equation modeling (SEM) and deep learning neural network (DLNN) hybrid. This could provide valuable guidance to policy makers and to employers for the formulation of training and development programs that could hasten the use of software and bridge the digital divide. Similarly, this research could bridge the gap between software engineering and ergonomics which could contribute to enhanced efficiency, improved user satisfaction, and the development of a more competitive software testing tool [37].

2. Conceptual Framework

There were several studies that provided insights on the integration of TAM and TTF, sole framework, or integrated with another model. The literature review table provided covered their usage and the positive results in relation to technology adoption, actual use, and performance impact for technology-related system evaluation. Presented in Table 1 is the information from the different studies.

Table 1. Literature review.

Author	System/Model	Method	Purpose	Findings
Davis and Venkatesh [15]	Evaluation of TAM	Experimentation	To evaluate the presence of bias and utility of TAM.	It was explained how the groupings based on the initial construct should be utilized involving perceived usefulness and perceived ease of use to behavioral intentions and then actual use evaluation.
Taherdoost [16]	Review of TAM	Comparative study among adoption and acceptance models	To give light on the advantages and disadvantages of different models.	Several theories and models may be utilized to completely understand and measure the issue at hand.
Lai [17]	Review of TAM and other models	Literature review	To provide insights on the different theories and models for technology-related study evaluation.	It was suggested that the usage of the models and theories depends on the need of the study. The applicability of additional latent variables and integration would lead to a more comprehensive analysis.
Hancerliogullari Koksalmis and Damar [18]	Evaluation of SAP ERP adoption using TAM	Structural equation modeling	To determine factors affecting SAP ERP adoption in the workplace.	The implications of their results presented recommendations for future studies and linked the theory and practice in SAP ERP systems by proposing a model, which offers novel perceptions for engineering managers who are in search of adopting the SAP ERP system.
Shamsi et al. [19]	TAM and job-demand resources theory	Structural equation modeling	To analyze work-related well-being during the COVID-19 pandemic.	Their results showed how the application of integrated theories would holistically measure the target object. It was seen that mental workload, perceived ease of use, and perceived usefulness impacted the engagement and usage of technology among users.

Table 1. *Cont.*

Author	System/Model	Method	Purpose	Findings
Wu and Tian [20]	TTF model	Structural equation modeling	To evaluate enterprise social networks.	They found that TTF alone is not sufficient to completely measure other aspects of social networks. For the applicability of their study, they utilized the DeLone and IS Success Model. The results presented TTF variables and perception of usage among users influenced their continuous usage.
Wu et al. [21]	Integration of TTF, initial trust model, and the extended unified theory of acceptance and use of technology	Structural equation modeling	To evaluate cross-border mobile payments.	They utilized three models to consider all areas of trust, behavior, and new technology adoption. The study found that initial trust, performance expectancy, effort expectancy, facilitating conditions, price value, task technology fit, and initial trust have significant effects on use intention.
Chuenyindee et al. [22]	Online learning set-up actual use using TAM, TTF, and the system usability scale	Structural equation modeling	To evaluate technology adoption in the online learning set-up during the COVID-19 pandemic.	Their study considered only the technology characteristics and TTF latent variable as deemed necessary. The results presented that TAM and TTF integration would suffice in measuring new technology usage and adoption among users. It could therefore be deduced that latent variables in this model are flexible depending on the applicability of the technology being evaluated.
Sun et al. [23]	TAM and TTF integration for ERP systems	Structural equation modeling	To evaluate factors affecting the intention to use and actual use of Enterprise Resource Planning (ERP) systems.	It was seen and suggested that TTF is a more crucial indicator than actual IT use in realizing the performance impacts on organizations.
Diar et al. [24]	TAM, TTF, and Delone and McLean IS Success Model for procurement systems	Structural equation modeling	To evaluate the determinant factors of SIRUP implementation in Indonesia and its impact on procurement personnel performance.	The results showed that a good fit between task and technology, usage experience, and user satisfaction impact individual performance.
Sari et al. [25]	TAM, TTF, and IS model	Structural equation modeling	To evaluate use of e-budgeting software in the Ministry of Public Works and Housing in Indonesia.	In their study, TTF influenced perceived usefulness and perceived ease of use, and these two factors affect the intention and actual use of the software.

Table 1. *Cont.*

Author	System/Model	Method	Purpose	Findings
Wallace and Sheetz [26]	TAM	Structural equation modeling	To evaluate software usage.	They have implied that understanding adaptability enables the development of software that is perceived as useful and easy to use.
Yen et al. [27]	Integration of TAM and TTF	Structural equation modeling	To assess factors affecting user acceptance of a new wireless technology.	Their study presented how TAM is used to measure user acceptance while TTF is used to measure technology fit for a certain task. The integration of both TAM and TTF can holistically measure behavioral and interpersonal variables.
Wu et al. [28]	Integration of TAM and TTF	Structural equation modeling	To measure continuance intention and usage of MOOCs.	Their study justified the usage of the integrated models for comprehensive measurement and understanding of behavioral intentions and actual use of technology. Their study also presented how development of technology and software needs evaluation, especially for newly established systems.
This study	TAM and TTF integration	Structural equation modeling and deep learning neural network	To evaluate factors affecting career shifters' adoption and actual use affecting their perceived performance impact for software testing tools.	Perceived Ease of Use confirmed the Technology Acceptance Model framework as a strong predictor of Actual System Use. Intention to Use, Perceived Usefulness, Actual Use, and Subjective Norm were also significant factors affecting Perceived Performance Impact. This study is the first to explore the career shifter's use of software testing tools in the Philippines. The framework would be very valuable in enhancing government policies for workforce upskilling, improving the private sector's training and development practices, and developing a more competitive software testing tool that would hasten users' adaptability. Lastly, the methodology, findings, and framework could be applied and extended to evaluate other technology adoption worldwide.

Figure 3 represents the proposed conceptual framework of the study. This research combines an extended Technology Acceptance Model (TAM) and Task Technology Fit (TTF) as used in similar studies [26,28,38,39]. The integration of the TAM and TTF captures two aspects of using technology, namely cognitive beliefs, and how the use of technology improves job performance [40,41].

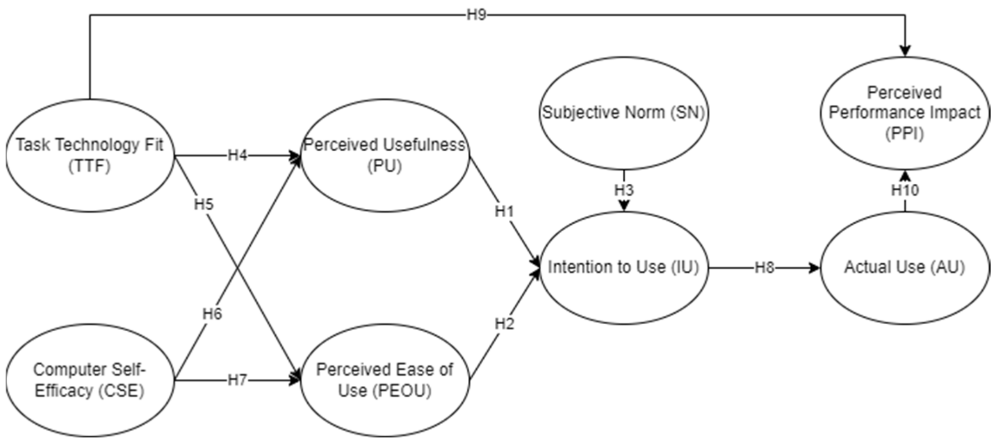

Figure 3. Proposed framework.

Perceived Usefulness (PU) is the perception of the extent to which using a system will improve his/her performance [15]. A system that is perceived to be used advantageously influences the use–performance relationships positively [16,26]. PU is proven to have a positive influence on the intention to use technology [25,28,36,37,42]. The perceived usefulness of software testing tools can be described as the factor that forms the behavioral intent to use the technology. Yeh and Teng [43] proved how PU is one of the most important factors that significantly affect the adoption of technology use. Amoako-Gyampah [44] also utilized the TAM and presented how PU is one of the key significant factors affecting an individual's intention to use a system. Thus, it was hypothesized that:

H1. *Perceived usefulness has a positive influence on the individual's intention to use the software testing tool.*

Perceived Ease of Use (PEOU) is the person's belief in his/her capability to perform a certain task using a particular system [38]. It also pertains to the perceived level of difficulty in using information technology [19]. PEOU affects the behavioral intention to use [25,26,38,42]. Similarly, PEOU was also seen to have a direct and significant effect on an individual's intention to use a system [44]. Contrary to the study of Wu and Chen [30], PEOU did not have a significant influence on intention to use due to the dependence of adoption on the perceived usefulness. However, Abdullah et al. [45] showed how PEOU is the contributing factor to the adoption and intention to use a system when users are relatively new to it. This shows that when users are new to using the system, PEOU is highly significant [11,13,30]. From this, it was hypothesized that:

H2. *Perceived ease of use has a positive influence on the individual's intention to use the software testing tool.*

Subjective Norm (SN) in this study is the user's behavior that is influenced by social motivation [30] such as people whom they value and who want them to use the technology [39]. This is similar to the UTAUT2 construct of social influence [32,46]. SN has an influence on the intention to use especially in mandatory settings [11,14,38,47]. However, it was indicated by different studies [30,31] that the strict implementation to use a system may not be sustainable among users, leading to a negative perception. Abdullah et al. [45] presented how having SN would help determine why users are influenced by their intention to use a system. Similarly, the study of Ong et al. [48] showed how people who are important to the users would affect the positive implication in the acceptance of relatively new technology. Therefore, SN is a latent variable that should be considered to determine its effect on an individual's intention to use software testing tools. As such, it was hypothesized that:

H3. *Subjective norm has a positive influence on the individual's intention to use the software testing tool.*

Task Technology Fit (TTF) is the measure to which the technology is able to support the individual in turning inputs into outputs [45]. The fitness of the function of technology with the requirements of the task determines its usefulness [39]. In the context of this study, TTF is the degree to which the individual believes that the tool he/she is using is fit to the job portfolio. Past findings have shown that TTF has a significant effect on PU and PEOU [25,28,38,49]. In addition, several studies have stated that when users are satisfied with the system usage due to PU and PEU, they would have a higher intention to use the system [50–52]. It could be stated that the influence of fit of the system for the intention to use would be inclined on the perspective of users with its usefulness and ease of use. For this construct, we have the following hypotheses:

H4. *Task technology fit has a positive influence on the individual's perceived usefulness.*

H5. *Task technology fit has a positive influence on the individual's perceived ease of use.*

Computer Self-Efficacy (CSE) is the individual's perception of his/her ability to perform specific tasks using a software package [40]. Computer confidence allows the user to have a positive attitude towards using the technology [53,54]. Similar to previous findings, it is expected that CSE will positively affect an individual's PEOU [42,45,55] and PU [55]. The study of Hasan [56] presented how CSE is primarily significant in the actual use of a system. Having experience in utilizing different software may ease an individual's perspective on the usage due to their ability to perceive a system to be easy and useful. Similarly, it could be deduced from several studies that knowledge and experience in the use of technology would lead to the actual use due to their perceived benefit [30,31]. Thus, CSE as an antecedent of PU and PEOU was hypothesized as:

H6. *Computer self-efficacy has a positive influence on the individual's perceived usefulness.*

H7. *Computer self-efficacy has a positive influence on the individual's perceived ease of use.*

Intention to Use (IU) is the intention of the individual toward using the technology [39,57]. IU is determined by two beliefs PU and PEOU [30,48]. It was stated that if the system is considered beneficial, easy to use, and has overall usability, then users would have a positive perspective on its actual usage. Several studies have presented a positive influence of IU on the actual use of different technologies, preceded by several factors under different fields of technology use [45,56,58–62]. Thus, it was hypothesized that:

H8. *Intention to use has a positive influence on the individual's actual use of the software testing tool.*

Perceived Performance Impact (PPI) pertains to the fulfillment of tasks by the user [42]. According to Goodhue and Thompson [63], a higher TTF leads to improved performance [39,52,63]. Past research has also stated that usage affects individual performance [18,57]. In this context, the perceived performance is the degree to which the use of the software testing tool enhances the quality of work by reducing mistakes, quicker completion of tasks, and boosting efficiency [52]. On another note, Actual Use (AU) has been seen to affect PPI directly. When users adopt the system being used, trust has been built in their usage and thus increases their performance impact [64]. In addition, it was explained that when users are able to trust and are satisfied with the system's actual use, their performance is influenced and has a positive impact on their perception [65]. As such, it was formulated that:

H9. *TTF has a positive influence on the individual's perceived performance impact.*

H10. *Actual use has a positive influence on the individual's perceived performance impact.*

3. Methodology

3.1. Structural Equation Modeling

Structural equation modeling (SEM) was used to examine the relationships between indicators and constructs [45]. SEM was run using AMOS version 21 with the Maximum Likelihood Estimation (MLE) approach. Similar to other technology-related studies that considered evaluation of actual use or performance impact, this study also considered the analysis of causal relationships using SEM. Prasetyo et al. [11] utilized SEM to determine organizational commitment to using technology for its perceived effectiveness in the Philippines. In addition, Chuenyindee et al. [30] and Yuduang et al. [31] considered SEM with the integrated framework to determine the actual use of a mobile application in Thailand. Lastly, Gumasing et al. [12] also considered utilizing SEM for the evaluation of behavioral intentions and actual use of an application. The indicators used to prove the adequacy of model fit were Goodness of Fit Index (GFI), Incremental Fit Index (IFI), Tucker Lewis Index (TLI), Comparative Fit Index (CFI), Normed Chi-squared ($\chi2/\mathrm{df}$), and Root Mean Square Error of Approximation (RMSEA). For GFI, IFI, TLI, and CFI, a value of 0.8 was considered good, for the Normed Chi-squared less than 3 was good, and for the RMSEA a value of 0.08 was acceptable [66,67].

However, several studies have criticized SEM for its limitations due to the presence of mediators. Woody [68] showed how the mediating effect may hinder the significance and relationship of the independent latent variable. In addition, Fan et al. [59] presented how the presence of a mediating effect may lead to preceding variables having little to no significance. Several studies [31,69] have considered the integration of SEM with other tools such as machine learning algorithms to provide justification for the results. Taking into account the study of Yuduang et al. [31], the evaluation of the actual use of an application was evaluated using SEM and neural network hybrid. Their results showed how the utilization of neural networks was able to present the highest importance compared to the causal relationship present in the SEM analysis. Significant factors were identified to be the same, however, relative importance was different. Thus, this study opted to utilize the SEM–DLNN hybrid for the analysis of the adoption and actual use of software testing tools amidst the COVID-19 pandemic.

3.2. Deep Learning Neural Network

Deep Learning Neural Network (DLNN) is a neural network that was inspired by how the brain receives signals from the neural in the human body. With several hidden layers present, DLNN can analyze the different nonlinear relationships present in the model [61,62], similar to the framework utilized in this study. Similarly, DLNN produces a higher accuracy rate due to the complex calculation present in the algorithm compared to other machine learning algorithms [70,71]. The datasets utilized came from all the responses made by the respondents. From 32 items and 150 respondents, a total of 4800 datasets were considered for the data preprocessing stage. Adopting the study of Ong et al. [48,72], data preprocessing using correlation analysis was conducted. The indicators were correlated and accepted values greater than 0.20 and less than 0.05 p-value [73]. Data aggregation utilized the mean result, and data normalization using min_max scalar was considered. With Python 5.1, a total of 4800 datasets were considered to evaluate factors affecting the actual use and adoption of software testing tools.

3.3. Participants

An online questionnaire was distributed from 24 September to 8 October 2021, to software testing community groups on different social media platforms. A total of 150 respondents answered through the use of Google forms. Respondents were informed that the data will be kept confidential and will be used for academic research only. The number of respondents was calculated using the Yamane Taro Formula following the paper of German et al. [74]. As indicated by the article of Uy [75], it was stated that 49% of employees in the Philippines considered career change which comprises approximately

30.7 million Filipinos [74]. The formula used is presented in Equation (1) with 0.10 degree of error (e) and 30.7 million as population size (N). This resulted in a sample size (n) of 100. This study was able to collect 150 samples which could be stated as a representation of the target measurement [66].

$$n = \frac{N}{N\,(e)^2} \tag{1}$$

Table 2 provides the profile of the participants. The majority of the respondents were from the age of 18 to 24 (53.33%) and 25 to 34 years old (41.33%). The table also presents that majority of the respondents have less than 1 year of experience using the software testing tools (74%). Since this study aimed to evaluate the actual use of software testing tools in the Philippines due to its relatively new system, little experience has been seen among available respondents. The data available for the evaluation would be critical to having a sustainable system developed for continuous patronage. Moreover, most of the respondents utilized the tool for more than 4 h (46.67%). The majority are daily users of the software testing tool (29.33%). Lastly, most of the respondents utilize Selenium IDE (35.15%) or Tricentis TOSCA (30.38%) in their software testing activities.

Table 2. Descriptive statistics of respondents (N = 150).

Measure	Value	N	%
Gender	Male	60	40.00%
	Female	90	60.00%
Age	18 to 24 years old	80	53.33%
	25 to 34 years old	62	41.33%
	35 to 44 years old	7	4.67%
	45 to 54 years old	1	0.67%
Software testing tool used	Tricentis TOSCA	89	30.38%
	Worksoft Certify	16	5.46%
	HP UFT	11	3.75%
	Katalon Studio Intelligent Test Automation	26	8.87%
	LEAPWORK	2	0.68%
	Selenium IDE	103	35.15%
	Others	46	15.70%
Experience using the software testing tool	Less than 1 year	111	74.00%
	1 to 2 years	23	15.33%
	2 to 3 years	7	4.67%
	More than 3 years	9	6.00%
How much time do I usually spend using the software testing tool?	Less than 1 h	16	10.67%
	1–2 h	33	22.00%
	3–4 h	31	20.67%
	More than 4 h	70	46.67%
Usage frequency	1–2 times a month	43	28.67%
	3–6 times a month	31	20.67%
	7–12 times a month	14	9.33%
	More than 12 times	18	12.00%
	Daily	44	29.33%

3.4. Questionnaire

The questionnaire is comprised of two parts. The first part includes seven (7) demographic profile questions such as career shifter identification, gender, age, tool used, experience, time spent using the software testing tools, and usage frequency. The second part has 32 items or indicators for the 8 latent variables. The items were measured on a 7-point Likert scale. The integrated extended Technology Acceptance Model (TAM) and Task Technology Fit construct was the framework used. The items were developed based on previous studies (See Appendix A). The 7-point Likert scale is structured as follows:

1—Strongly Disagree, 2—Disagree, 3—Somewhat Disagree, 4—Neither Agree nor Disagree, 5—Somewhat Agree, 6—Agree, 7—Strongly Agree.

4. Results

Figure 4 presents the initial model of the study. All paths were found to be significant with a p-value less than 0.05 [66]. Unfortunately, based on the assessment of the proposed framework's fit with the data gathered, removing paths PU → IU, TTF → PEOU, and CSE → PU (p-values close to 0.05) would improve the adequacy of model fit following the suggestion of Hair [66]. To have an acceptable proposed model, the mentioned relationships which are close to having p-value = 0.05 were removed. As seen in Figure 2, the relationship has values indicating the beta coefficient. This pertains to the strength and sensitivity among all direct relationships in the model. TTF has the highest and strongest relationship on PPI, followed by TTF on PU, CSE on PEOU, and the rest in sequential and descending order. Following this is Table 3 with the model modification results.

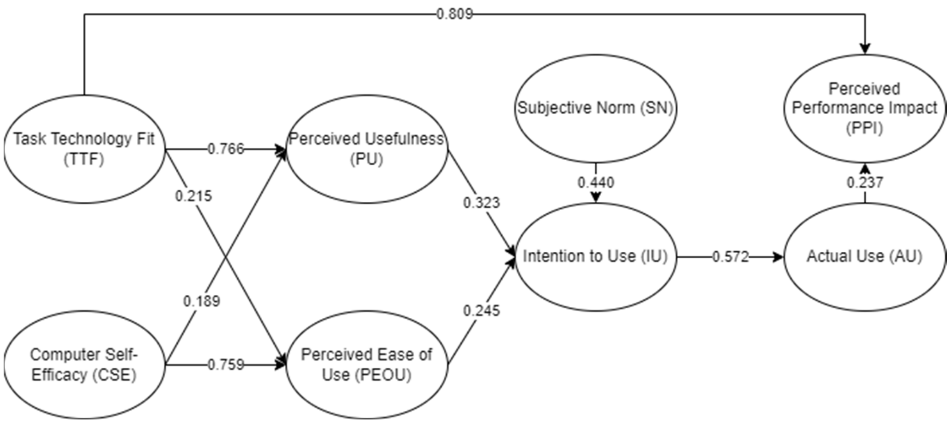

Figure 4. The initial conceptual framework.

Table 3. Model modification.

Hypothesis		Preliminary Model		Final Model	
		β	*p*-Value	β	*p*-Value
1	PU → IU	0.323	0.050	-	-
2	PEOU → IU	0.245	0.037	0.268	0.054
3	SN → IU	0.440	0.040	0.604	0.002
4	TTF → PU	0.766	0.001	0.826	0.002
5	TTF → PEOU	0.215	0.050	-	-
6	CSE → PU	0.189	0.050	-	-
7	CSE → PEOU	0.759	0.002	0.849	0.002
8	IU → AU	0.572	0.001	0.641	0.001
9	TTF → PPI	0.809	0.002	0.810	0.003
10	AU → PPI	0.237	0.004	0.194	0.016

With the adjustment made, the model was run to present the finalized SEM for assessing factors affecting actual use affecting perceived performance impact on career shifters' software testing tools. The final model was derived and presented in Figure 5. Based on the final SEM, the highest relationship is present with CSE and PEOU, followed by TTF on PU, TTF on PPI, SN on IU, IU on AU, PEOU on IU, and AU on PPI. Studies such as that of Woody et al. [68] and Fan et al. [76] explained that the difference in the relationship and sensitivity of the beta coefficient is affected by the mediating factors which could be further validated using other techniques [69]. To completely present the result, the fitness measures of the final model are shown in Table 4.

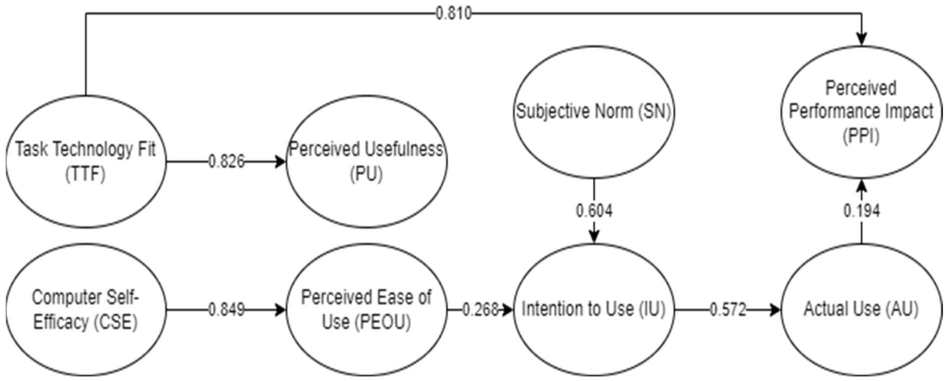

Figure 5. Final structural equation model.

Table 4. Final model fit.

Goodness of Fit Measures of the SEM	Parameter Estimates		MinimumCut-Off	Recommended by
	Initial	Final		
Normed Chi-squared ($\chi 2/df$)	2.701	2.035	<3	Hair et al. [66]
Goodness of Fit Index (GFI)	0.681	0.840	>0.80	Gefen et al. [77]
Root Mean Square Error of Approximation (RMSEA)	0.107	0.063	<0.08	Fabrigar et al. [67]
Incremental Fit Index (IFI)	0.815	0.888	>0.80	Gefen et al. [77]
Tucker Lewis Index (TLI)	0.795	0.875	>0.80	Gefen et al. [77]
Comparative Fit Index (CFI)	0.813	0.887	>0.80	Gefen et al. [77]

On the other hand, Table 5 presents the mean and standard deviation for each of the items in the questionnaire with the indicator AU2 having the highest standard deviation at 1.805 and PU4 with the lowest deviation from the mean value of 0.817. Moreover, the construct validity and reliability are presented in Table 6. According to Hair et al. [66], factor loadings should be at least 0.5 to be considered significant. Results showed that factor loadings were higher than 0.5. Thus, the indicators represented the selected latent.

Table 5. Mean, standard deviation, construct validity, and reliability.

Latent Variable	Indicator Variables	Mean	Standard Deviation	Standardized Loadings	Average Variance Extracted (AVE)	Construct Reliability (CR)
PU	PU1	6.320	0.885	0.820	0.711	0.907
	PU2	6.327	0.987	0.761		
	PU3	6.367	0.839	0.925		
	PU4	6.513	0.817	0.858		
PEOU	PEOU1	6.040	0.982	0.761	0.635	0.874
	PEOU2	5.740	1.161	0.769		
	PEOU3	5.827	1.073	0.883		
	PEOU4	5.587	1.100	0.768		
TTF	TTF1	6.320	0.892	0.750	0.738	0.918
	TTF2	6.280	0.970	0.896		
	TTF3	6.273	1.049	0.912		
	TTF4	6.360	0.854	0.869		
CSE	CSE1	5.380	1.257	0.852	0.712	0.908
	CSE2	5.320	1.183	0.885		
	CSE3	5.507	1.191	0.782		
	CSE4	5.607	1.129	0.852		

Table 5. *Cont.*

Latent Variable	Indicator Variables	Mean	Standard Deviation	Standardized Loadings	Average Variance Extracted (AVE)	Construct Reliability (CR)
SN	SN1	5.627	1.144	0.506	0.515	0.797
	SN2	5.487	1.345	0.509		
	SN3	6.260	1.155	0.910		
	SN4	6.400	1.017	0.863		
IU	IU1	6.253	0.978	0.832	0.575	0.842
	IU2	6.153	0.947	0.828		
	IU3	6.433	0.789	0.703		
	IU4	6.460	0.841	0.653		
AU	AU1	5.547	1.464	0.873	0.700	0.903
	AU2	5.153	1.805	0.908		
	AU3	4.940	1.708	0.801		
	AU4	5.513	1.370	0.755		
PPI	PPI1	5.840	1.171	0.774	0.580	0.847
	PPI2	6.313	0.970	0.729		
	PPI3	6.400	0.882	0.783		
	PPI4	6.253	1.024	0.760		

Table 6. Convergent validity using MSV and ASV.

Latent	AVE	MSV	ASV
PU	0.711	0.527	0.353
PEOU	0.635	0.546	0.336
TTF	0.738	0.607	0.432
CSE	0.712	0.480	0.376
SN	0.515	0.430	0.405
IU	0.575	0.381	0.328
AU	0.700	0.392	0.392

In addition, Table 5 also shows that the average variance extracted (AVE) of the latent variables was higher than 0.5. This translates to a close relation of indicator to latent construct [66]. Moreover, the construct reliability (CR) of latent variables was higher than the 0.7 benchmark value. Lastly, Cronbach's alpha per latent variable also had values greater than 0.70. This indicates the existence of internal consistency which means the indicators represent the same latent construct [66].

The Maximum Shared Variance (MSV) and the Average Shared Variance (ASV) were calculated to verify the results of the findings. Presented in Table 6 are the results compared to the AVE values. It was stated that when the MSV and ASV values are lower than the AVE, the results showed convergent validity and internal consistency [78].

To further evaluate the validity of the results, the discriminant validity tests using the Fornell–Larcker criterion (FLC) and Heterotriat–Monotrait ratio (HTMT) were considered [79]. Presented in Table 7 are the FLC results. It could be seen that the values on the diagonal values are larger than the ones from the horizontal values. Following the study of Yang et al. [80], it was stated that FLC is considered a conservative method for analyzing the correlation of the latent variables with the square root of the AVE values. Having a higher value from the diagonal schema would present validity [66].

In addition, the HTMT ratio was calculated as seen in Table 8. Based on the results, all values are within the threshold set, 0.85 [81] or 0.90 [78]. HTMT is considered a Monte Carlo simulation correlation-based analysis that evaluates the validity of the constructs. With all values having less than 0.85, it could be stated that consistency and validity are achieved for the results of this study [12].

Table 7. Fornell–Larcker criterion.

Latent	PU	PEOU	TTF	CSE	SN	IU	AU	PPI
PU	0.843							
PEOU	0.543	0.797						
TTF	0.726	0.546	0.883					
CSE	0.533	0.739	0.599	0.844				
SN	0.668	0.582	0.656	0.693	0.722			
IU	0.564	0.479	0.585	0.527	0.629	0.758		
AU	0.496	0.598	0.65	0.634	0.623	0.524	0.836	
PPI	0.594	0.495	0.779	0.586	0.656	0.617	0.626	0.762

Table 8. Heterotrait–Monotrait ratio.

Latent	PU	PEOU	TTF	CSE	SN	IU	AU
PEOU	0.612						
TTF	0.845	0.609					
CSE	0.652	0.827	0.655				
SN	0.826	0.746	0.844	0.811			
IU	0.780	0.697	0.824	0.714	0.752		
AU	0.714	0.821	0.820	0.852	0.794	0.593	
PPI	0.802	0.668	0.803	0.780	0.848	0.802	0.698

The associations between the constructs of the final model were evaluated based on the measure of statistical significance (p-value < 0.05) and their standardized loadings. Table 9 presents the direct, indirect, and total effects of latent variables. For the direct effects, Subjective Norm had a higher positive effect on Intention to Use (β = 0.604, p = 0.002) than Perceived Ease of Use (β = 0.268, p = 0.050). Task Technology Fit has a higher positive effect on Perceived Usefulness (β = 0.826, p = 0.002) than its effect on Perceived Performance Impact (β = 0.810, p = 0.003). Actual Use has a positive direct effect on Perceived Performance Impact at 0.194 with a significance of 0.016. The direct path of Computer Self-efficacy to Perceived Ease of Use has the highest loading in the model (β = 0.849, p = 0.002). This indicates that Hypothesis 2, PEOU on IU is accepted; similarly, Hypotheses 3, 4, 7, 8, 9, and 10 were also accepted; while hypothesis 1 was not. Summarized in Table 9 are the accepted hypotheses, beta coefficients, and p-values.

Table 9. Hypotheses and results.

Hypothesis	Variables	Direct	p-Value	Results
1	*PU → IU*	*0.323*	*0.058*	*Not Supported*
2	PEOU → IU	0.268	0.050	Supported
3	SN → IU	0.604	0.002	Supported
4	TTF → PU	0.826	0.002	Supported
5	*TTF → PEOU*	*0.215*	*0.051*	*Not Supported*
6	*CSE → PU*	*0.759*	*0.055*	*Not Supported*
7	CSE → PEOU	0.849	0.002	Supported
8	IU → AU	0.641	0.003	Supported
9	TTF → PPI	0.810	0.003	Supported
10	AU → PPI	0.194	0.016	Supported

For the indirect effects, while Computer Self-Efficacy has a higher effect on Actual Use (β = 0.146, p = 0.040) than on Perceived Performance Impact (β = 0.028, p = 0.029). However, it proved not significant for its effect on the intention to use Subjective Norm's indirect effect on Actual Use (β = 0.387, p = 0.001) and was higher than its effect on Perceived Performance Impact (β = 0.075, p = 0.014). The indirect effect of Perceived Ease of Use on Actual Use (β = 0.172, p = 0.042) was higher than its effect on Perceived Performance

Impact (β = 0.033, p = 0.031). Lastly, the indirect effect of Intention to Use to Perceived Performance Impact had a β value of 0.124 with a statistical significance of 0.015. The path analysis for the indirect effect is presented in Table 10.

Table 10. Path analysis.

Variables	Direct	p-Value	Indirect	p-Value	Total	p-Value	Results
CSE → IU	*No path*	-	*0.227*	*0.057*	*0.227*	*0.057*	*Not Supported*
CSE → AU	No path	-	0.146	0.040	0.146	0.040	Supported
CSE → PPI	No path	-	0.028	0.029	0.028	0.029	Supported
SN → AU	No path	-	0.387	0.001	0.387	0.001	Supported
SN → PPI	No path	-	0.075	0.014	0.075	0.014	Supported
PEOU → AU	No path	-	0.172	0.042	0.172	0.042	Supported
PEOU → PPI	No path	-	0.033	0.031	0.033	0.031	Supported
IU → PPI	No path	-	0.124	0.015	0.124	0.015	Supported

Deep Learning Neural Network

To validate the findings of SEM, DLNN was considered in this study. A total of 12,600 runs were conducted to determine the optimum parameters. At 150 epochs and 10 runs, pre-combination was conducted [48,73]. With the utilization of Python 5.1, parameters such as Relu and Sigmoid for the activation functions of the hidden and output layers were considered with Adam as the optimizer. The DLNN produced an accuracy rate of 96.32%. Presented in Figure 6 is the optimum DLNN model considered in this study, run at an 80:20 training and testing ratio.

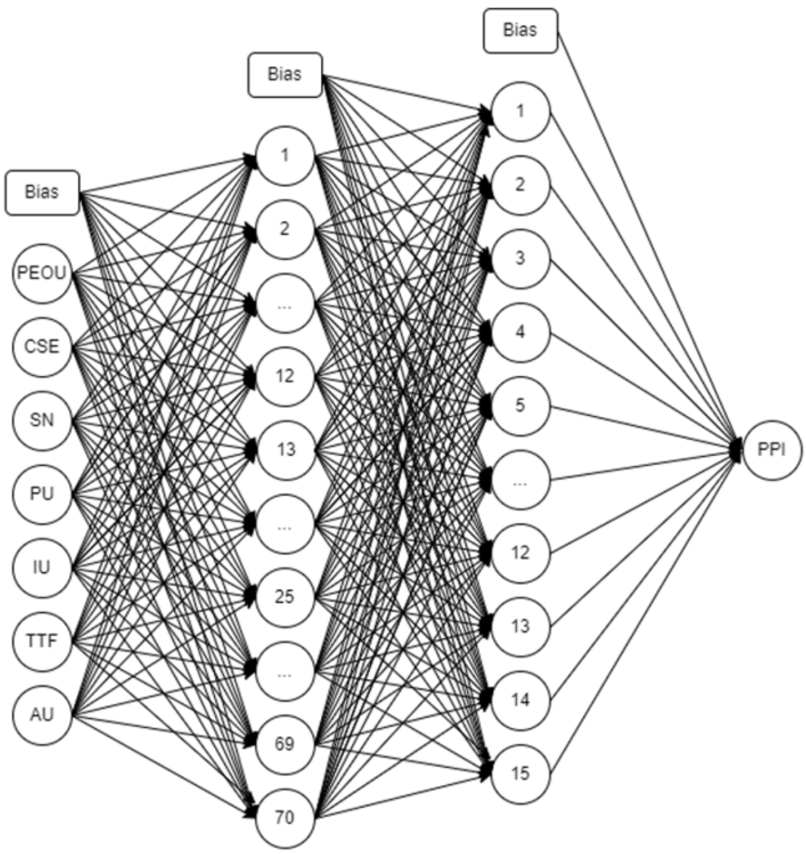

Figure 6. Optimum DLNN model.

Following the suggestion of Ong et al. [73] and Yuduang et al. [31], the average testing accuracy results pertain to the significance ranking of the latent variables considered.

Presented in Table 11 are the summarized results of training and testing accuracies with their respective standard deviations. It could be deduced that actual use is primarily affected by TTF, followed by CSE, PEOU, IU, PU, AU, and SN as the least. As seen from the sequence, the relative significant sequence was evidently different from SEM. Following the suggestion of different studies [68,76], the presence of mediation between PU, PEOU, and IU may have caused the difference in results. The confirmation using the score of importance as presented in Table 12 was conducted.

Table 11. DLNN results.

Latent	Average Training	StDev	Average Testing	StDev
TTF	**86.55**	**3.651**	**95.90**	**3.944**
CSE	83.93	6.324	93.31	5.384
PEOU	81.33	4.989	92.00	5.784
IU	86.78	5.207	91.31	4.666
PU	74.48	5.332	87.45	4.522
AU	76.59	4.762	81.67	3.480
SN	78.79	5.809	80.04	4.584

Table 12. Score of importance.

Latent	Importance	Score (%)
TTF	**0.205**	**100**
CSE	0.197	96.2
PEOU	0.196	95.7
IU	0.188	91.8
PU	0.183	89.5
AU	0.181	88.3
SN	0.173	84.6

The score of importance presented a similar sequence of significance to the DLNN results. Thus, the discussion will follow the sequence from the machine learning algorithm, integrating the findings from SEM.

5. Discussion

Software testing tools are extensively used in testing activities of software development. The software offers a variety of functionality that meets business needs. The shift of industries to high-tech solutions was accelerated by the pandemic. This brought the need for people with technological skills and competencies. Job seekers and career shifters are challenged to adopt the use of digital tools such as software applications. In this study, the extended Technology Acceptance Model (TAM) and Task Technology Fit (TTF) were used to determine the factors affecting a career shifter's adoption and use of software testing tools amidst the COVID-19 crisis in the Philippines.

Task Technology Fit (TTF) positively affects the Perceived Usefulness (PU) and Perceived Performance Impact (PPI). The DLNN result presented TTF as the most significant factor affecting PPI. The TTF's positive effect on PU is consistent with previous findings [25,38,49]. It was seen that the software the users were utilizing fit the job at hand and could help them finish their respective tasks. Since people find the technology being used as necessary to complete the task it presents as the most contributing factor. This means individuals perceive improved performance because of the good fit between the task and the tool used [24]. The study of Elci and Abubakar [82] considered TTF in their study for use of online technology during the COVID-19 pandemic. It was seen that TTF and engagement were key factors affecting higher performance upon using a technology. Rai and Selnes [83] showed a 79% adoption of technology when it is deemed fit for the user to complete a task. Goodhue and Thompson [63] highlighted that despite the relevant fit of technology, the need to assess the components of the technology is needed. This presents the need to consider factors under TAM to holistically cover why users would adequately choose which technology would be best. The current study showed Computer Self-Efficacy as the second-highest contributing factor.

CSE has a significant positive influence on Perceived Ease of Use. As expected from previous studies, CSE plays an important role in influencing the PEOU of a particular technology [42,45,55]. This relationship considers that the higher the computer self-efficacy the more the individual will use the technology [55]. People were seen to be more confident in utilizing the technology at hand, possess sufficient skills to employ tasks, and show comprehension despite the availability of user manuals. This finding was also in accordance with earlier research [42,84]. Salloum et al. [42] stated that individual preference and cultural differences affect an individual's CSE. It has also been argued that the high effects of CSE on PPI may be due to the users' development with technology [85]. The relative findings would be dependent on the demographics. Since this study considered users who are equipped with knowledge and skills, it presents how CSE is an important and significant factor. However, caution for technology adoption should be taken when considering demographics with fewer skills for actual use of systems. In line with business sectors, Henry and Stone [86] highlighted how CSE provided a correlation with outcome expectancy and individual level of analysis. Thus, it could be highlighted that to achieve a positive output, both TTF and CSE among users should be highly considered.

Perceived Ease of Use (PEOU) was found to have a positive effect on Intention to Use (IU) and was seen to be the third most important latent variable. Users find it easy to use and operating it does not hinder the output of the users. Similar to previous studies, PEOU increases the attitude towards technology use [26,28,39,54,87,88]. The easier it is to use a system, the higher the intention of an individual to use the system [25]. These results also align with a positive intention to use technology. Intention to Use (IU) is found to positively influence the actual use of the technology, fourth among the latent variables. According to Davis and Venkatesh [15], IU is the best predictor of Actual Use of a system. The indicators of this study presented that users have the intention to use a system when it is available, even indicating future intentions to use testing tools in the future. Previous studies have indicated the same results [46,55,84]. The study of He et al. [89] instigated PEOU and CSE highlights the user's IU with technology and system usage. Their study showed that when self-efficacy when considering a system is present, people would consider the ease of use of a certain technology. This is true especially when the task at hand is easily performed with the help of the adopted technology [90]. A higher IU is evident when users find the system highly applicable and benefits them in terms of output [30].

Perceived Usefulness (PU) was found to be a contributing factor affecting PPI. This is in line with present studies relating PU as being a significant predictor of IU [28,38,39,42,55,87,91]. In the workplace settings, the study of Sun et al. [23] and Sari et al. [25] found that PU significantly affects intention to use. It was explained that when the technology at hand is applicable, there is a high PU for the achievement of output [23]. It was seen that users find that using the system improves their job performance, effectiveness, and productivity. Highlighting the findings, Wallace and Sheetz [26] presented how the adoption of technology has been widely applied but has been under-evaluated before utility. They presented how properties that are desirable based on software measures to achieve the task needed should be considered in a business setting to achieve higher PU which will lead to actual use. With the five highly significant factors explaining its relation to PPI, the importance has been evident of why there is actual use, leading to a positive PPI.

Actual Use (AU) has a positive significant effect on perceived performance impact (PPI). According to Goodhue and Thompson [63], the performance impact is a function of both TTF and AU. This was supported in both the AU–PPI and TTF–PPI relationships. The users have indicated that they utilize the tools frequently, considering the multiple features, and are dependent on the testing tools. Similarly, the study of Sun et al. [23] stated that the actual use of Enterprise Resource Planning Systems software positively affects individual performance. With the dependence on technology, AU has been evidently significant among users. The study by Awan et al. [92] highlighted that when users constantly use a system, a positive relationship between performance management and employee performance was seen. In accordance, Butt et al. [93] presented the correlation of TTF and AU among online users when the technology affects them positively with regard to their task at hand, satisfaction, and performance. Thus, the more beneficial the technology is towards the task, the higher AU could be seen.

Lastly, Subjective Norm (SN) has a positive effect on the intention to use the software testing tool and was the least, but a high, significant score of importance. This is consistent with expectations that SN influences Intention to Use [23,47]. However, in the study of McGill and Klobas [46] which was in the voluntary setting, SN was not found to influence the utilization of technology. Davis and Venkatesh [47] emphasized that Subjective Norm affects intention when usage is mandatory and when experience is at the early stages. In this study, the majority have less than 1 year of experience in using the software testing tools and the use is attributed to mandatory settings [16]. Thus, it explains why SN was the least significant factor affecting PPI. In addition, Davis and Venkatesh [15] also highlighted how SN could be disregarded after the establishment of usage and adoption of technology among users.

Overall, it could be deduced that users would continue using and promote the utility when it is fit to the task at hand, easy to use, beneficial, and applicable. This will lead users to realize their future targets, acquire new knowledge and skills, and promote the completion of tasks. The need to enable assessed and tested technology among users is needed to enhance compatibility and promote positive output, especially in the business setting. It could be posited that wrong testing tools despite the advanced technology will not create a positive outcome among users and the business. This will therefore lead to negative effects ranging from satisfaction to profitability.

5.1. Practical Implications

The primary objective of this paper was to determine factors through the integrated extended TAM and TTF model that affect a career shifter's adoption and use of software testing tools in the Philippines during the COVID-19 pandemic. Based on the findings, our study has several important implications. In mandatory settings and in accordance with a previous study [26], the easier it is to use a software testing tool the more likely it is to be adopted. The "internet-savvy" Filipino [94] gives value to the societal perspective, as subjective norm was found to directly affect the intention to use and indirectly actual use and perceived performance impact. Similarly, previous studies have stated that TTF has even more relevant effects when used in less voluntary situations such as the workplace [23,47]. Findings imply that TTF highly influences the individual's perceived capability to deliver outputs. This indicates that being "internet-savvy", users were able to identify how the software being utilized was applicable and corresponds to the need for tasks. It was implied that for a system or technology to be highly impactful on performance, ease of use and usefulness should be highly considered. Enhancing computer skills build confidence that allows an individual to perceive a tool as easy to use [91]. This may imply that Filipinos perceive computer self-efficacy as significant towards recognizing software testing tools as easy to use.

Finally, the findings of this study offer a deeper understanding to job seekers, employers, government, and software designers. This could be useful in improving the adoption and use of technology that could benefit both policy-making and private institutions to ease the hiring requirements and hasten resource deployment. This can be a basis for initiating training courses and maximizing the use of social media channels to enhance adaptability and the use of software testing tools. The growing demand for IT professionals such as software testers and the evident skills gap implies that job seekers, career shifters, employers, governments, and software developers must collectively exert efforts to bridge the digital divide. This research gives importance to the growing market for IT professionals as the global workplace transitions to digital solutions.

5.2. Limitations and Future Research

Despite the contributions of the study, there were several limitations. First, the study only utilized the TAM and TTF approach. However, there are several other adoption models [16] such as considering individual characteristics that could further explain the cultural context [46]. The behavioral aspect such as the consideration of the Theory of Planned Behavior and the use of the System Usability Scale may be considered as an extension or analysis. Second, the emphasis was given to the role of being a software tester and the use of software testing tools. Future research can compare other roles in the software development or IT industry which can also be available to job seekers and career shifters such as software engineering, data analysis, data science, and the like. Third, this study considered only a self-administered survey. More findings may be capitalized on by researchers and developers if qualitative analysis from interviews will be conducted. For instance, the information regarding software testing tools list and how much time they spend on it. Other factors may also be classified upon the curation of interview answers. Lastly, the study only considered those with experience thus results focused on those who are knowledgeable with testing tools. Future studies may compare and contrast those without experience and perform clustering techniques to segregate the findings. Moreover, task characteristics such as automation, resource sharing, multitenancy, internal expertise, and remote implementation may be considered as extended variables for evaluation when the technology being utilized is widely accustomed. In addition, other variables such as free maintenance and management, on-demand self-service, broad network access, rapid elasticity, resource pooling, virtualization, and service-oriented architecture may be considered once the establishment and seniority are available for technology testing.

6. Conclusions

The ongoing COVID-19 pandemic resulted in high unemployment rates. As a consequence, more Filipinos are changing careers to earn a living [7,8]. As more businesses shift to technological solutions [6], and as the Philippines has over 400 software firms [94], considering shifting careers in the IT industry offers stability and growth. However, high-demand roles such as software testing require a specific skill set. Career shifters and job seekers must be able to adapt and use these technologies to match the skill requirement. Past studies have been conducted to understand and measure the adoption and use of technology through acceptance and usability frameworks. In this study, the combined TTF and extended TAM framework were used to determine the factors affecting a career shifter's adoption and use of software testing tools.

The results of the structural equation modeling (SEM) and deep learning neural network (DLNN) exhibited that Task Technology Fit had a higher effect on perceived performance impact than actual use. Task Technology Fit highly influenced the perceived usefulness of a software testing tool. A user's computer self-efficacy is a strong predictor of an individual's perceived ease of use. The perceived ease of use and perceived usefulness confirmed its significance to influence intention to use in relation to the TAM framework. In the workplace setting, subjective norm was found to have a significant effect on the intention to use the software testing tool. The actual use of the tool was significantly affected by intention to use. The findings implied that for a system or technology to be highly impactful on performance, ease of use and usefulness should be highly considered. Enhancing computer skills build confidence that allows an individual to perceive a tool as easy to use.

This research is the first to have explored the acceptance of software testing tools among career shifters and software testers in the Philippines. This framework can be beneficial in enhancing training and development and software testing tool design which can accelerate an individual's adoption and use. This study offers a deeper understanding to job seekers, employers, government, and software designers. This could be useful in improving the adoption and use of technology that could benefit both policy-making and private institutions to ease the hiring requirements and hasten resource deployment. Lastly, the methodology, findings, and framework could be applied and extended to evaluate other technology adoption worldwide.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in this study (FM-RC-22-11).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Instrument

Construct	CODE	Indicator	Source
Perceived Usefulness (PU)	PU1	Using the software testing tool improves my job performance.	[12,31]
	PU2	Using the software testing tool increases my productivity.	[12,31]
	PU3	Using the software testing tool enhances my effectiveness in my job.	[12,31]
	PU4	I find the software testing tool useful in my job.	[12,31]
Perceived Ease of Use (PEOU)	PEOU1	My interaction with the software testing tool is clear and understandable.	[12,31]
	PEOU2	I find the software testing tool to be easy to use.	[12,31]
	PEOU3	I find it easy to get the software testing tool do what I want it to do.	[12,31]
	PEOU4	Learning to operate the software testing tool is easy for me.	[15]
Task Technology Fit (TTF)	TTF1	The use of the software testing tool is fit for the requirements of my job role.	[22]
	TTF2	The software testing tool I am using is suitable for helping me complete my tasks.	[22]
	TTF3	The software testing tool is necessary to my work tasks.	[44]
	TTF4	The software testing tool is fit to my job.	[44]
Computer Self-Efficacy (CSE)	CSE1	I feel confident in the utilization of the software testing tool even if there is no one to assist me.	[28]
	CSE2	I have sufficient skills in using the software testing tool.	[28]
	CSE3	I feel confident in using the software testing tool even if I have only online instructions/manual.	[28]
	CSE4	I feel confident in using the software testing tool's features.	[28]
Subjective Norm (SN)	SN1	People who influence my behavior think that I should use the software testing tool.	[12,31]
	SN2	People who are important to me think that I should use the software testing tool.	[12,31]
	SN3	My company has been helpful in the use of the software testing tool.	[45]
	SN4	My company has been supporting the use of the software testing tool.	[45]

Construct	CODE	Indicator	Source
Intention to Use (IU)	IU1	Assuming I have access to the software testing tool, I intend to use it.	[31]
	IU2	Given that I have access to the software, I predict that I would use it.	[31]
	IU3	I intend to use software testing tool in the future.	[22]
	IU4	I will continue using the software testing tool increasingly in the future.	[22]
Actual Use (AU)	AU1	I use the software testing tool frequently	[28]
	AU2	I use the software testing tool on a daily basis.	[28]
	AU3	I depend on the software testing tool.	[30]
	AU4	I use multiple features of the software testing tool.	[30]
Perceived Performance Impact (PPI)	PPI1	Using the testing tool helps me realize my future targets.	[28]
	PPI2	Using the testing tool helps me acquire new knowledge.	[28]
	PPI3	Using the testing tool helps me acquire new skills.	[28]
	PPI4	Using the testing tool helps me make it easier to complete my tasks.	[28]

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