Avoidance Behaviour towards Digital Crowdsourcing Platforms: A Preliminary Study among New Freelancers

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Abstract

New innovations and the expansion of the Internet have led to a rising trend in crowdsourcing platforms, which has, in turn, changed the business model from face-to-face services to platform-based services. This trend heavily relies on digital experts and skilled users in an interconnected ecosystem. While the literature has widely discussed the concepts and benefits of digital crowdsourcing towards employers and employees, the majority of today's crowdsourcing platforms face challenges and various potential threats, especially among newcomers in this digital world. The work investigates the perceived threats towards the avoidance motivation and avoidance behavior among newcomers to digital crowdsourcing platforms. An online survey was performed using Structural Equation Modelling (SEM) among 142 newly-registered students who were actively involved in the digital workforce climate. The statistical results confirmed that avoidance motivation leads to avoidance behavior, while perceived threats and self-efficacy lead to perceived threats. Additionally, perceived threats are influenced by perceived severity. Contradictly, perceived threats did not significantly influence perceived susceptibility. The findings are useful not only for digital crowdsourcing platforms but also for policymakers.

Keywords: Digital crowdsourcing, freelancer, avoidance behaviour, threat avoidance, TTAT theory, digital workforce

1. Introduction

Technology has shaped today's employment trends by integrating flexibility from various angles in terms of job creation, job offers and work schedules. In the digital world, anyone with a high degree and digital expertise can become a digital worker. Many digital jobs are offered via these digital platforms, which provide benefits to digital workers and individuals or small organizations who have limited budgets but require experts. Among the top platforms in digital tasks are Freelancer.com, Guru.com, and Upwork.com, among others. These platforms offer thousands of digital jobs for unemployed freelancers worldwide, which are as easy as data entry jobs, to a more complex jobs, such as web programming, 3D visualization, apps development or business consulting.

By applying this digital workforce concept, organizations or employers will have cost-saving benefits from various angles, such as labor, time and budget. For digital workers themselves, working as freelancers will allow them to manage their careers by being more time-oriented and self-oriented, which in turn will lead to a better work-life balance. However, working in a digital environment requires someone who possesses technical skills and domain-specific knowledge, as well as high social intelligence, to succeed, despite the benefits of flexibility.

Although these digital workforce platforms provide opportunities and have a significant impact on society, some of the digital workforce environment elements may be overlooked. Only a few studies in the area have focused on newcomers in the digital crowdsourcing world. They are considered inexperienced, and the highest risk group for frauds and cyber threats. Despite these security issues, newcomers may also develop a new kind of digital etiquette that may build the expectation of 'always available online', which may lead to burnout and retention problems. Thus, these challenges may affect their motivation and behavior in certain situations, causing them to avoid digital work. The drive to make use of technologies and work online, according to Fogg (2009), may be triggered by pairs of opposites, such as enjoyment or discomfort, hope or fear, and approval or resistance.

The growing number of fake projects or scammers available on almost all crowdsourcing websites is one of the challenges faced by digital workers (Dawson & Thomson, 2018). The emphasis on factors influencing digital workers' avoidance behavior against digital threats has been less discussed in previous research. Digital workers should be solely responsible for the decision of whether to accept or reject the work offered by taking into account all the opportunities and risks they may face.

The next part of this article describes the conceptual context and theoretical structure for the current research and associations to the development of the theory. This is accompanied by an explanation of the approaches used for data collection. This paper outlines the measurement and structural model, and the evaluation of several hypotheses. The last section presents a discussion and concludes with some suggestions for future research.

2. Literature Review

2.1 Avoidance Behavior

Avoidance behavior is a type of behavior or action that a person takes to prevent something he/she dislikes or to escape from difficult thoughts and feelings. Burnout, anxiety, and panic disorder are examples of behaviors that can contribute to a devastating effect on an individual. Crowdsourcing platforms comprise a group of people from various places who are unknown to each other. Thus, for some, this situation makes them feel odd and anxious. Due to the risk of putting confidential information in public, some digital workers tend to avoid disclosing some of their valuable profile information to be published on the platform. A digital worker who owns this behavior will also tend to avoid applying for an online job, or withdraw from the job assigned to him/her by clients, due to the lack of confidence in finishing the sophisticated project. Instantaneously, those individuals with no understanding of privacy and ethics are more likely to suffer from data misuse than the gain of exchanging information online (Shahrom *et al.*, 2017).

In examining the avoidance behavior, the Technology Threat Avoidance Theory (TTAT) has been applied in various areas, including crowdsourcing, health care, cybersecurity, and information systems (Liang and Xue, 2009). The TTAT demonstrates that people first assess the existence and extent of threats, and then consider what they should do to mitigate possible risks when facing IT threats. The TTAT points out that consumers can assess the extent of the avoidability of risks on the basis of the efficiency of the safeguard measures and the degree of self-efficiency in the execution of the safeguard measures. Threats are minimised by consumers by enforcing security mechanisms, since they feel they can remove these threats (Liang and Xue, 2010).

2.2. Perceived Susceptibility

In the field of information technology, perceived susceptibility is linked to a person's subjective perception of the probability of danger or technological threats. The susceptibility is described as the conviction that malicious technology is harmful (Liang and Xue, 2009). An individual creates a view of a threat when they feel that a malicious program is likely to target them, and will avoid the threat to prevent danger. For example, digital workers may face two types of scammers: those who post jobs online but have no further discussion about the offer (low susceptibility), or those who require a digital worker to deposit money upon starting the project (high susceptibility). Hence, the perceived susceptibility of these negative consequences will develop into a threat perception behavior. Therefore, the following hypothesis was formulated.

H1: Perceived susceptibility has a positive relationship on perceived threat.

2.3. Perceived Severity

Perceived severity can be described as the negative effects of an event or outcome. This concerns the risks they will encounter in the future, and the consequences that can be associated to an expected event that may occur in the present or future. Chen et al. (2015) found that perceived severity is a tacit awareness of the probability and the detriment of the person's actions. He or she may perceive the severity of accepting offers, which might increase the chances of becoming a scam victim (Sticca and Perren, 2013). In crowdsourcing scenarios, digital workers are more likely to change the severity level when the risk is high, and thus influence the threat perception. Therefore, the following hypothesis was formulated.

H2: Perceived severity has a positive relationship on perceived threat.

2.4. Perceived Threat

As persuasive applications continue to generate millions of investments, the issue of the manipulation of personal data by ubiquitous technologies is a major one. The level of satisfaction new digital workers feel as they join the digital workforce influences their decisions to divulge their data. However, perceived threats occur when they sense a malicious application as being dangerous. Thus, it provides them the initial motivation to commence avoidance behavior from using the application. Therefore, the following hypothesis was formulated.

H3: Perceived threat has a positive relationship on avoidance motivation.

2.5. Self-Efficacy

To successfully become a freelancer in crowdsourcing platforms, a digital worker must possess digital self-efficacy that gives him/her the confidence to execute any given tasks, besides taking the necessary risks (Cassidy & Eachus, 2002). Self-efficiency is closely associated with one's own confidence in the ability to carry out actions in particular situations, and to achieve a mission (Bandura, 1986). Self-efficacy is best described as an individual's confidence in taking safeguard measures, which are important elements of avoidance motivation. Self-efficacy can also enhance positive outcome expectations, since a person who has a high confidence level and self-esteem is more likely to feel optimistic about his or her role as a skillful digital worker (Lent, Ireland, Penn, Morris, & Sappington, 2017). The self-efficacy within a digital workforce involves personal trust in the worker's ability to perform digital workforce jobs. Digital workers with high self-efficacy can confidently apply for jobs related to their skills, face challenges when they encounter difficult tasks, and complete their jobs based on their level of expertise, rather than choose to avoid problems (Bandura, 2010; Barker, 2017). Therefore, the following hypothesis was formulated.

H4: Self-efficacy has a positive relationship with avoidance motivation.

2.6. Avoidance motivation

Motivation for avoidance is a part of natural human behavior in which psychological, physiological, and social factors appear to resist unpleasant stimuli. When faced with obstacles, individuals in uncertain environments usually struggle with avoidance motivation (Sadler, Shluzas, Blikstein, & Katila, 2015). For example, in a crowdsourcing platform, due to plenty of competitors applying for the same job, a new digital worker will most commonly feel pressured and tend to avoid or reject the job offer, due to his/her anxious decisions, regardless of whether the job is from a verified client. According to Schunk and DiBenedetto (2016), a lack of self-efficacy is also an influential avoidance motivation. It can affect the effort people make, and how long they remain in facing challenges (Schunk, 2012). Therefore, the following hypothesis was formulated.

H5: Avoidance motivation has a positive relationship with avoidance behavior.

3. Methodology

To examine the perceptions of threat avoidance, a quantitative survey study was conducted among a group of newcomers in the digital work force who actively participated in crowdsourcing platform environments. As there is no way to obtain a list of the population participating in digital platforms for online jobs, a non-probability sample technique was applied. Using a purposive sampling technique, only individuals who had experience using digital platforms in performing digital workforce tasks were identified, while others were omitted from the study.

To assess the sample size, the GPower program (Erdfelder, Faul and Buchner, 1996) was used to measure the minimum sample size with a predictive power of 0.95. Calculations indicated that with a limit of two predictors, the necessary sample size was 107 (i.e. effect size is 0.15) (Cohen, 1992).

A survey was autonomously conducted to obtain data from the respondents. A five-point Likert questionnaire was used to collect data for each research model construct. All instruments were adapted from prior work (Alomar, Alsaleh and Alarifi, 2019) that underlies from the Technology threat avoidance theory (TTAT). The process of distributing and collecting questionnaires involved groups of social science undergraduate students who underwent digital workforce programs and were enrolled in the subject for nearly four months. The program required the students to apply for jobs via bidding or contest applications. To ensure each of the students is familiar with the digital workforce concept working environment, each of them was required to apply for at least 100 job applications during the course, to ensure they had sufficient experience as digital workers. An online sample of 142 eligible responses was received at the end of the semester, as show in Table 1.

Table 1: Respondent Profiles

Variables	***Category***	***Frequency***	***Percentage***
Gender	Female	120	84.5
	Male	21	14.8
Age	<21 years old	3	2.1
	21-23 years old	128	90.1
	24-25 years old	7	4.9
	> 25 years old	4	2.1
The platform used for digital work	Freelancer.com	135	95.1
	Freelancing.com	1	0.7
	PeoplePerHour	3	2.1
	Upwork	1	0.7
	Others	1	0.7
Level of experience in digital work	Beginner	120	84.5
	Intermediate	21	14.8
	Advanced	1	0.7
Type of jobs applied in the freelance platform	Business and Accounting	1	0.7
	Data Entry	40	28.2
	Graphical Design	65	45.8
	Sales and Marketing	9	6.3
	Translation	9	6.3
	Typing	12	8.5
	Writers/Content Development	1	0.7
	Others	5	3.5

The survey questionnaires acceded to a total of 142 individuals. Table 1 provides the respondents' demographic profiles. As shown in the table, 84.5% were females and 14.8% were males. Dividing the age factor into several ranges, the findings revealed that 2.1% were under the age of 21, 35.9% were 21-22, 54.2% were 21-22, 35.9% were 21-22, and just 2.1% were above the age of 21. In terms of digital workforce activity, Freelancer.com is the largest platform used, with 95.1%, followed by other sites of fewer than 5% each. The majority of the respondents (84.5%) were newcomers in digital work experience. This result was expected, as all of the selected respondents were undergraduate students being exposed to the digital work environment for the first time. Graphics design (45.8%), followed by data entry (28.2%) and typing (8.5%)

were among the top-ranked jobs applied during the four-month session. The remainder of the job types were less prominent among the students, such as sales and marketing, translation, business and accounting, and writers/content creation. The next section presents the validity and reliability evaluation of these frameworks within a theoretical context.

4. Findings

4.1. Common Method Variance

Where data are gathered from self-reported questionnaires and, in particular, from the same person, the common method variance must be examined (Podsakoff et al., 2003). The effects of the common method variance can be diminished in several processes. This work focused on both the methods and the statistical approaches before and after data collection. The Harman Single-Factor Test was employed to statistically test the common method variance (CMV). The single-factor test results revealed the highest variation of one factor, as explained by the 27.67% variation, demonstrating that the data had no issue with CMV.

4.2. Model Validation

The structural equation modelling technique (Hair et al., 2014) was used to validate the model using the SmartPLS3 program (Ringle, Wende and Becker, 2015). All constructs were measured with reflective indicators. The measurement model (i.e. validity and reliability of measures) was evaluated using the recommended two-stage analytical method (Anderson & Gerbing, 1988). This was followed by structural model evaluation (i.e. testing the hypothesized relations).

4.3. Assessment of Measurement Model

The convergent validity was tested in the assessment of the measurement model. This involved calculating the loading of the indicators, followed by average variance (AVE) and composite reliability (CR). The loading indicators for all indicators surpassed the recommended 0.5 value (Hair, Hult, Ringle, & Sarstedt, 2017). However, three items (i.e. SUCS2, SUCS3, and SUCS4) were omitted due to low factor loading. The AVE range was between 0.557 and 0.737, and surpassed the cut-off value beyond 0.50. The CR was between 0.7 and 0.935, which met the suggested 0.7 value (Hair et al., 2017).

Table 2 presents a description of the measurement model results. Furthermore, the discriminating validity (Fornell and Larcker, 1981) was assessed. The square roots of the AVE (in bold) are shown in Table 3 to be higher than the off-diagonal correlation values and implied sufficient discriminant validity. Thus, it should be assumed that there was sufficient validity and reliability of the measurements used in this analysis.

Table 2: Measurement Model

Constructs	***Items***	***Loadings***	***AVE***	***CR***
Avoidance Behavior	AB1	0.813	0.637	0.841
	AB2	0.764		
	AB3	0.817		
Self-Efficacy	EFF1	0.634	0.532	0.772
	EFF2	0.818		
	EFF3	0.811		
Avoidance Motivation	MOT1	0.756	0.657	0.905
	MOT2	0.816		
	MOT3	0.782		
	MOT4	0.838		
	MOT5	0.857		
Perceived Severity	SEV1	0.673	0.503	0.832
	SEV2	0.763		
	SEV3	0.824		
	SEV4	0.539		
	SEV5	0.715		
Perceived Susceptibility	SUCS1	0.717	0.509	0.804
	SUCS5	0.654		
	SUCS6	0.829		
	SUCS7	0.641		
Perceived Threats	THR1	0.817	0.712	0.908
	THR2	0.903		
	THR3	0.877		
	THR4	0.773		

** SUCS2, SUCS3, and SUCS4 were deleted due to low loading

Table 3: Discriminant Validity

	1	***2***	***3***	***4***	***5***	***6***
1. Avoidance Behavior	**0.798**					
2. Avoidance Motivation	0.709	**0.811**				
3. Perceived Susceptibility	0.224	0.323	**0.714**			
4. Perceived Severity	0.373	0.406	0.649	**0.709**		
5. Perceived Threats	0.47	0.411	0.395	0.541	**0.844**	
6. Self-Efficacy	0.505	0.513	0.44	0.487	0.517	**0.73**

Note: Diagonal (bolded) values are the AVE's square root, while off-diagonal values are correlations.

4.4. Assessment of Structural Model

After the measurement model was established, the analysis moved to structural model evaluation. The existence of strongly-correlated constructs were tested using a collinearity test. As shown in Table IV, a collinearity test was conducted by calculating the variance factor inflation (VIF) values. The results showed that the inner VIF values of all contructs, ranging from 1.120 to 2.434, were far below the proposed threshold (Diamantopoulos and Siguaw, 2006), which indicated that multi-linearity was not a problem in this study.

Next, as suggested by Hair et al. (2017), the hypothesis formed for this study was tested by running a resample 500 bootstrapping procedure. Figure 1 shows structural modelling assessments exhibiting the results of the various hypotheses assessments, each of which was confirmed. Overall, perceived susceptibility failed to predict perceived threats. Therefore, H1 was not supported (β=0.075, t=0.794). Perceived severity predicted perceived threats, and so H2 was confirmed (β=0.492, t=4.772, $p < 0.001$). The results were also similar for perceived risks and performance, all of which significantly avoided motivation. Therefore, both H3 and H4 confirmed (β=0.200, t=1.679, $p<0.001$, and β=0.410, t=3.810, $p<0.01$ respectively). Finally, avoidance motivation substantially predicted avoidance behaviour. Therefore, H5 was accepted (β=0.709, t=14.857, $p<0.001$).

The findings further described the exogenous constructs collectively, which explained the endogenous construct variance. According to Cohen (1988), the R^2 value for endogenous latent variables varies from zero to one (i.e. 0.26 substantial, 0.13 moderate, and 0.02 weak). Figure 1 shows that 29.6% of the variation in perceived threats can be explained by perceived susceptibility and perceived severity. Meanwhile, 29.2% of the variation was explained by perceived threats and self-efficacy, in terms of motivation for avoidance. Subsequently, the motivation for avoidance explained 50.2% of this variation in avoidance behavior. The evidence showed that the R^2 values had a substantial degree of explanatory capacity, which was demonstrated by a significant model (Cohen, 1988).

The effect sizes (f^2) were calculated to assess the impact of exogenous latent constructs on endogenous latent constructs (weak, moderate, or substantial) using the guidelines defined by Cohen (1988), in which the f^2 values of 0.02, 0.15, and 0.35 reflect small, medium and large effects respectively. The results indicated that perceived susceptibility had no effect in producing the R2 for customer satisfaction (0.005). However, perceived severity (0.199) had a medium effect on perceived threats. Meanwhile, perceived threats had a small effect (0.041) and self-efficacy had a medium effect (0.174) towards avoidance motivation. In addition, avoidance motivation had a large effect on avoidance behavior (1.008).

Besides that, the predictive relevance of the model was verified. The model relevance to endogenous structures is predictive if the Q^2 value is greater than 0 (Hair et al., 2017; Ramayah et al., 2018). Overall, the Q^2 values of perceived threat (0.188), avoidance motivation (0.168), and avoidance behavior (0.285) indicated that the model had sufficient predictive relevance. In addition, the avoidance motivation had a large effect on avoidance behavior (1.008).

Table 4: Structural Model

	Relationship	**Std. Beta**	**Std. Error**	**t-value**	**p-value**	**LL**	**UL**	**Decision**
H1	Perceived Susceptibility -> Perceived Threats	0.075	0.095	0.794	0.214	-0.098	0.221	Not Supported
H2	Perceived Severity -> Perceived Threats	0.492	0.103	4.772	p<0.001	0.287	0.643	Supported
H3	Perceived Threats -> Avoidance Motivation	0.200	0.119	1.679	0.047	0.035	0.416	Supported
H4	Self-Efficacy -> Avoidance Motivation	0.410	0.107	3.810	p<0.001	0.217	0.577	Supported
H5	Avoidance Motivation -> Avoidance Behavior	0.709	0.048	14.857	p<0.001	0.611	0.771	Supported

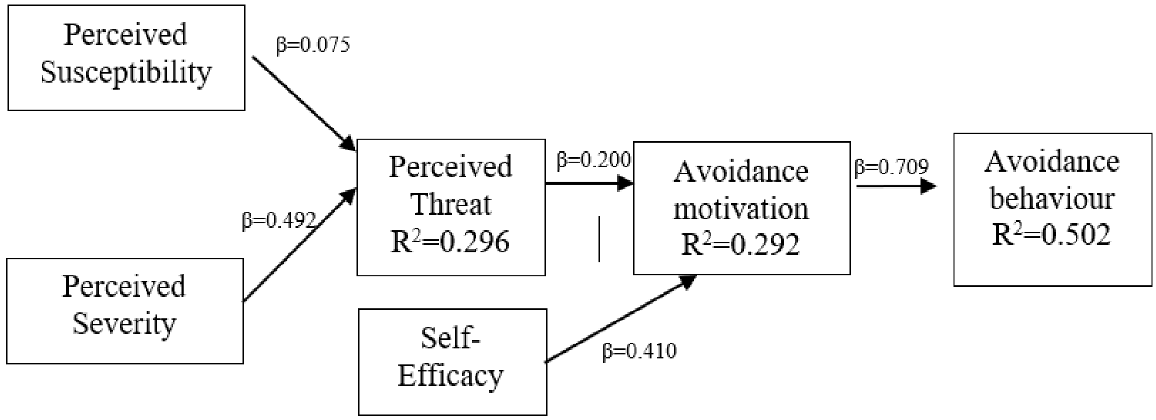

Fig. 1 Hypothesis Testing

5. Discussion and Conclusions

This article presents the outcomes of an empirical study that investigated the key factors behind the avoidance behavior towards digital crowdsourcing platforms among new crowd workers. This empiric investigation confirmed most of its key statements. The findings are in line with and echo the findings by Liang and Xue (2010) that avoidance behavior leads to avoidance behavior. However, contrary to the original hypothesis, it was also found that increased levels of perceived susceptibility do affect perceived threats. This is a good indication, which shows that young digital workers or millenial digital workers in Malaysia are actually alert on the potential risks that they face in digital crowdsourcing. As new comers in digital workforce platforms, dealing with various kinds of risks is inevitable, and experience is required in order to identify genuiene clients and project tasks.

In addition, both constructs significant and substantially improved the overall R^2 value obtained in the analysis. The findings revealed that perceived threats and self-efficacy have a positive effect on the avoidance motivation towards avoidance behavior. This is in line with prior work (Alomar, Alsaleh and Alarifi, 2019). Self-efficacy had a higher impact on avoidance. This is indeed critical, especially for newcomers in digital crowdsourcing, when they have more knowledge on the risks and potential threats of these platforms. Hence, they will be more confident to use these platforms. Overall, the results of the model effectively accounted for a substantially larger percentage of the variance in avoidance behavior.

5.1. Research Limitations and Future Directions

As this study was conducted in Malaysia, the findings may not be applicable to other regions. It is proposed that future analyses should be recreated, considering the current research setting, but in the context of other countries. Future studies should explore how digital employees' avoidance activity adaptation can be measured over time using a longitudinal approach. Moreover, as the analysis only centralized new entrants in the crowdsourcing world, the findings may vary from digital workers those who have experience in the modern crowd-sourced community, and in using these platforms and handling consumers.

5.2. Conclusion

There is no doubt that digital workers will build a new way of working that can leverage the full value of technology. However, in most cases, the only fraction towards the new concept of employability in the crowdsourcing world is the fraction of its potential to be exploited. The findings of this study demonstrate that avoidance motivation leads to final avoidance behavior towards rejecting tasks in crowdsourcing platforms, with both perceived threats and self-efficacy leading to avoidance motivation. Although perceived severity leads to perceived threats, no evidence was found on how perceived susceptibility leads to perceived threats. More evidence is needed on the scam trends and activities in the real digital working environments to provide guidance, especially to novice digital workers who are still new.

References

Alomar, N., Alsaleh, M., & Alarifi, A. (2019). Uncovering the predictors of unsafe computing behaviors in online crowdsourcing contexts. *Computers and Security*, *85*, 300–312. https://doi.org/10.1016/j.cose.2019.05.001

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Chen, L. M., Cheng, W., & Ho, H. C. (2015). Perceived severity of school bullying in elementary schools based on participants' roles. *Educational Psychology*, *35*(4), 484–496. https://doi.org/10.1080/01443410.2013.860220

Cohen, J. (1988). Statistical power analysis for the behavioral sciences. *Statistical Power Analysis for the Behavioral Sciences*. https://doi.org/10.1234/12345678

Cohen, Jacob. (1992). Statistical Power Analysis. *Psychological Bulletin*, *1*(3), 98–101. https://doi.org/10.1037/0033-2909.112.1.155

Dawson, J., & Thomson, R. (2018). The future cybersecurity workforce: Going beyond technical skills for successful cyber performance. *Frontiers in Psychology*, *9*(744). https://doi.org/10.3389/fpsyg.2018.00744

Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management*. https://doi.org/10.1111/j.1467-8551.2006.00500.x

Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior Research Methods, Instruments, & Computers*, *28*(1), 1–11. https://doi.org/10.3758/BF03193146

Fogg, B. (2009). A Behavior Model for Persuasive Design. In *Proceedings of the 4th international Conference on Persuasive Technology* (pp.1–7). https://doi.org/10.1145/1541948.1541999

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*. https://doi.org/10.2307/3151312

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks: Sage*. https://doi.org/10.1016/j.lrp.2013.01.002

Hair, J. F. J., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2014). *A Primer on Partial Least*

Squares Structural Equation Modeling (PLS-SEM). Long Range Planning (Vol. 46). https://doi.org/10.1016/j.lrp.2013.01.002

Liang, H., & Xue, Y. (2009). Avoidance of information technology threats: A theoretical perspective. *MIS Quarterly: Management Information Systems*, *33*(1), 71–90. https://doi.org/10.2307/20650279

Liang, H., & Xue, Y. (2010). Understanding security behaviors in personal computer usage: A threat avoidance perspective. *Journal of the Association for Information Systems*, *11*(7), 1. https://doi.org/10.17705/1jais.00232

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Ramayah, T., Jacky, C., Chuah, F., Ting, H., & Memon, M. A. (2018). *Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3.0. Handbook of Market Research* (2th Editio). Pearson Malaysia Sdn Bhd. https://doi.org/10.1007/978-3-319-05542-8_15-1

Ringle, C., Wende, S., & Becker, J. (2015). SmartPLS 3. *Retrieved From*. https://doi.org/http://www.smartpls.com

Shahrom, M., Kassim, E. S., Humaidi, N., & Zamzuri, N. H. (2017). A captology study on behavior model for persuasive ubiquitous technology. *International Journal of Machine Learning and Computing*, *7*(5), 162–166. https://doi.org/10.18178/ijmlc.2017.7.5.640

Sticca, F., & Perren, S. (2013). Is Cyberbullying Worse than Traditional Bullying? Examining the Differential Roles of Medium, Publicity, and Anonymity for the Perceived Severity of Bullying. *Journal of Youth and Adolescence*, *42*(5), 739–750. https://doi.org/10.1007/s10964-012-9867-3

Shahrom, M. *et al.* (2017) ‘A captology study on behavior model for persuasive ubiquitous technology’, *International Journal of Machine Learning and Computing*, 7(5), pp. 162–166. doi: 10.18178/ijmlc.2017.7.5.640.

Sticca, F. and Perren, S. (2013) ‘Is Cyberbullying Worse than Traditional Bullying? Examining the Differential Roles of Medium, Publicity, and Anonymity for the Perceived Severity of Bullying’, *Journal of Youth and Adolescence*, 42(5), pp. 739–750. doi: 10.1007/s10964-012-9867-3.