# Blockchain Technology Adoption: Examining the Fundamental Drivers

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## ABSTRACT
Identifying and quantifying the drivers for adopting blockchain technologies are important for developing effective launch plan. Technology Acceptance Model (TAM) and its derivatives have been used for this purpose. However, some of these models only use a few standardized, predetermined independent variables to collectively represent the drivers. Low predictive power of TAM leads to questions on whether this restriction may detrimentally constrain the exploration of other driving factors. Some other extended models with higher $R^2$ are considered impractical and lack of theoretical foundations. This paper demonstrates that reasonable predictive power can be achieved even with simple, practically implementable model when research targets are sampled and segmented properly. By employing a more fundamental theory, this study has also included additional variable that would normally not be considered in TAM.

## CCS Concepts
**• Social and professional topics→ Professional topics**

## Keywords
Blockchain; Technology Acceptance; Reasoned Action; Planned Behavior

## 1. INTRODUCTION
Numerous researchers and consultants have analyzed and predicted the path of blockchain technology adoption based on technical advantages and values. Business strategies are hence derived [1-6]. However, fewer works have been done to understand the adoption from user behavior perspectives. Among the available studies, most of them use Technology Acceptance Model (TAM) to investigate the adoption behavior [7-9]. While TAM has been widely used for analyzing technology adoption, its predictive power has also been widely criticized [10-19]. To improve predictive power, extensions of TAM such as Unified Theory of Acceptance and Use of Technology (UTAUT) have been proposed [20]. These models give higher $R^2$ but being challenged for artificially introducing numerous moderators to achieve the results [21,22]. The excessive number of variables would also make UTAUT impractical for real-life researches. This study briefly examines the cause of apparent low $R^2$ in TAM and, by properly defining scope and sampling, demonstrates that reasonably high $R^2$ can be achieved with simple and implementable model under practical business environment.



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## 2. RELEVANT THEORIES
It is a common belief that attitude towards a certain behavior determines the actual action to perform or not perform that behavior. Theory of Reasoned Action (TRA) points out that human performing a particular behavior is influenced not only by his or her attitude towards that behavior, but also a subjective norm about that behavior [23]. Subjective norm refers to the subject's belief of what other relevant people think about the behavior. The theory explains many apparently inconsistent behaviors found in social science research [24]. As a further refinement, the Theory of Planned Behavior (TPB) has been developed to account for the subject's volition control. This is achieved by adding a component known as perceived behavioral control to TRA [25, 26].

The importance of TRA / TPB is that effect or strength of each driver for a particular behavior can be verified and quantified. This would be very useful for understanding barriers to a desirable behavior, and hence developing appropriate strategies to encourage it. Quit smoking, avoid drug use, treat illicit alcohol consumption are well-known applications of TRA / TPB in health sector [27-29]. In early smoking cessation campaigns, health hazards were emphasized. However, effectiveness was low. By using TPB, researchers identified that many smokers already had very high awareness about these negative health impacts and wanted to quit (i.e. a positive attitude towards quit smoking), but would not able to control their own behavior to stop smoking due to influences of subjective norm (e.g. what would their smoking friends think if he or she quit) and perceived behavioral control (e.g. low self-efficacy). Surprisingly, the behavior of "attempt to quit smoking" correlates much heavier to subjective norm and perceived behavioral control than to attitude [27, 30]. With these discoveries, later campaigns put more attentions to change subjective norm (e.g. emphasize supports from family and friends) and enhance perceived behavioral control (e.g. reinforce self-confidence), and subsequently achieved better results [27, 30]. The theory is equally applicable to behavioral investigation in technology sector. Adoption of energy services company in heavy industry, for example, has been analyzed and policy recommendations have been made accordingly [31].

Derived from TRA, Technology Acceptance Model (TAM) assumes the perceived usefulness of a technology and perceived ease of use can predict the actual use via attitude towards using [32]. This assumption is questionable because the connection between attitude towards using a technology and the actual use can be affected by factors not controllable by the potential user. If the user cannot make the final decision to adopt a certain technology, his attitude towards using this technology is obviously not a reliable predictor of adoption. In fact, researchers have pointed out that while TAM may reasonably predict user's intention, predictive power for actual use is low [10-19]. Effect of decision autonomy is illustrated in Section V.

A further problem is the effects of subjective norm in TRA model had been ignored in early TAM, although the construct has been added back in later versions of TAM [33]. It is worth pointing out that TRA concerns about decision of an individual and, as discussed above, subjective norm has an important role in many cases. Without this construct, it is expected that the model's predictive power will be reduced. This inference is consistent with most observations in [10-19].

To account for user's inability to make final adoption decision, moderators are introduced [20,33]. However, this approach has been criticized for being artificially increasing the $R^2$ without solid theoretical foundation [22]. Furthermore, adding numerous variables to the model has made it rather impractical in many real-life business settings.

As an alternative, the perceived behavioral control construct in TPB could possibly account for user's inability to make final adoption decision. Some studies [34-36] compared the predictive power of TPB and TAM on actual use but results are not conclusive.

To provide reliable insights for business strategy development, user's inability to make final adoption decision must be accounted. On the other hand, model construction must be based on researches that can be practically implemented under real-life business constraints. As discussed in Section IV, this study collects data from seminar participants and therefore, in the interest of time, only modest number of Likert scale questions are asked. Instead of introducing moderators to improve $R^2$, an early segmentation is applied, followed by analyses that include some and all of the segments.

In this paper, adoption of blockchain technologies among small and medium size enterprises (SME) in Hong Kong is analyzed. Data was collected via questionnaire and has been segmented by the respondent's industry, company revenue, and ability to make decision for blockchain technology adoption. Through segmentation, user's ability/inability to make final adoption decision has been accounted and the initial model is built based on responses from those decision makers. Details are explained in section IV.

Given the issue of decision making has been addressed, simple TRA model is chosen for model development under practical data collection restrictions.

# 3. THE MODEL

## 3.1 Model Construction

A proposed TRA model is shown in Figure 1.

In this model, three constructs drive the behavior of blockchain technology adoption. They are:

USF = perceived usefulness

EOU = perceived ease of use

TRD = perceived trend

Other constructs, as defined in standard TRA, are:

ATT = attitude towards adoption

NOR = subjective norm of adoption

INT = behavioral intention to adopt

BHV = behavior to adopt

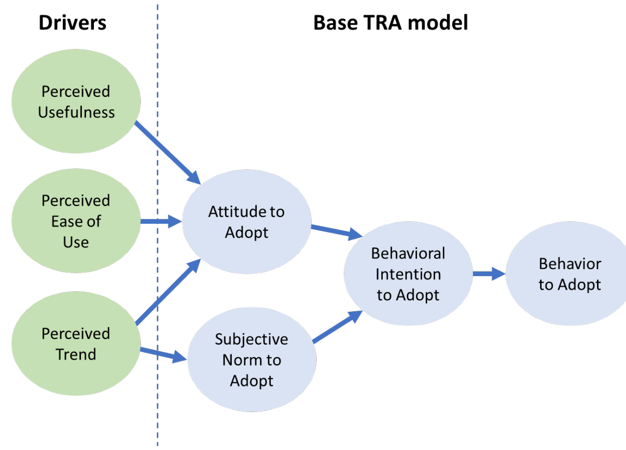


**Figure 1. TRA model for blockchain technology adoption**

## 3.2 Model Validation

Based on the model structure, mediation analysis is used to validate the model. Hypotheses in Table 1 are being verified.

**Table 1. Hypotheses for TRA blockchain adoption model**

| Hypothesis | | Description |
|---|---|---|
| H1 | H1a | USF and INT are positively correlated. |
| | H1b | ATT and INT are positively correlated. |
| | H1c | The relationship between USF and INT is mediated by ATT. |
| H2 | H2a | EOU and INT are positively correlated. |
| | H2b | ATT and INT are positively correlated. |
| | H2c | The relationship between EOU and INT is mediated by ATT. |
| H3 | H3a | TRD and INT are positively correlated. |
| | H3b | ATT and INT are positively correlated. |
| | H3c | The relationship between TRD and INT is mediated by ATT. |
| H4 | H4a | TRD and INT are positively correlated. |
| | H4b | NOR and INT are positively correlated. |
| | H4c | The relationship between TRD and INT is mediated by NOR. |
| H5 | H5a | ATT and BHV are positively correlated. |
| | H5b | INT and BHV are positively correlated. |
| | H5c | The relationship between ATT and BHV is mediated by INT. |
| H6 | H6a | NOR and BHV are positively correlated. |
| | H6b | INT and BHV are positively correlated. |
| | H6c | The relationship between NOR and BHV is mediated by INT. |

To obtain numerical values for validation, these constructs are measured via 20 variables listed in Table 2. Each variable is corresponding to a question on the questionnaire designed for this research. Respondents provide their answers by indicating whether they Strongly Agree (score=5), Agree (score=4), being Neutral (score=3), Disagree (score=2), or Strongly Disagree (score=1) to the statement of the question. Numerical averages of variables associated with each construct would be, subjected to Cronbach's Alpha test, used to represent the respondent's view about that construct.

**Table 2. Variables / questions for measuring the constructs**

| Construct | Variable | Description |
|---|---|---|
| USF | USF_1 | In our business, some process improvements CANNOT be made without blockchain technologies. |
| | USF_2 | Adopting blockchain technologies will enable our company to offer new products / services that CANNOT be provided in the past. |
| | USF_3 | Blockchain technologies can provide a justifiable return on investment in a reasonable period of time. |
| | USF_4 | In our sector, companies who have implemented blockchain technologies have gained competitive advantages. |
| EOU | EOU_1 | Blockchain technologies are safe and reliable. |
| | EOU_2 | For our business, there is no major operational barrier for adopting blockchain technologies. |
| | EOU_3 | Our employees can quickly cope with changes due to deploying blockchain technologies. |
| | EOU_4 | If needed, external implementation consultants are readily available at a reasonable fee. |
| TRD | TRD_1 | At a regional / country level, authorities are encouraging companies to adopt blockchain technologies. |
| | TRD_2 | Adopting blockchain technologies is becoming a trend in many business sectors. |
| | TRD_3 | More companies in OUR sector will adopt blockchain technologies in the NEAR future. |
| NOR | NOR_1 | Our customers would expect our company to use blockchain technologies. |
| | NOR_2 | Our suppliers would expect our company to use blockchain technologies. |
| | NOR_3 | Our employees would expect our company to use blockchain technologies. |
| ATT | ATT_1 | Blockchain technologies can improve our operation |
| | ATT_2 | In an overall sense, blockchain technologies are good for our company. |
| INT | INT_1 | I believe our company should implement blockchain technologies in NEAR future. |
| | INT_2 | I am actively cultivating agreement among other relevant members in the company to adopt blockchain technologies. |
| BHV | BHV_1 | We are working out / already have a implementing plan with budget for blockchain technologies. |
| | BHV_2 | We have spent / scheduled to spend remarkably on implementing blockchain technologies. |

Upon finishing data collection, the following analyses are performed in order to formally validate the model:

(i) Cronbach's Alpha – to verify if using numerical average of the variables to represent the construct is vital.

(ii) Correlation and Discriminant Validity – to verify the theoretically uncorrelated constructs are actually uncorrelated.

(iii) Mediation Test – to verify the hypotheses in Table 1 in order to valid the proposed TRA model.

(iv) Exploratory Analyses – to explore alternative model structure.

(v) Predictive Power – to illustrate changes in model predictive power when different segments of respondents are included

# 4. DATA COLLECTION

## 4.1 Tools for data collection

Starting February 2019, an anonymous questionnaire designed for this research had been distributed to audiences of a number of commercial seminars on information technology for SMEs in Hong Kong. The survey officially closed in July 2019. There are 23 questions on the questionnaire, with 20 questions directly corresponding to the variables on Table 2, and 3 questions for understanding the essential background of the respondent. These three questions are shown in Table 3. At the end of each seminar, a short briefing about this survey is provided. Then, the audiences are asked to spare about 10 minutes to fill out and return the questionnaire.

**Table 3. Additional questions about respondent's background**

| |
|---|
| Which of the followings best describe your business nature?<br>__ Manufacturing<br>__ Trading<br>__ Services<br>__ Retail<br>__ Others |
| You company's annual revenue is:<br>__ Under USD 5M<br>__ USD 5 - 25M<br>__ USD 25-50M<br>__ Over USD 50M |
| Concerning about evaluating and /or investing in blockchain technologies, you are:<br>__ the final decision maker<br>__ taking major responsibilities<br>__ regularly involved<br>__ occasionally involved<br>__ not involved |

While attaching survey to commercial seminars is helpful for securing a satisfactory respond rate, there are a few limitations that could affect the research quality.

(a) Length of the questionnaire – it is impractical to request respondent to answer many questions under this setting. Spending 10 minutes is probably the threshold. For TRA survey, using only 20 questions to valid a general model is challenging [37].

(b) Appropriateness of sample – this survey is about decision of adopting blockchain technologies. Not all seminar participants are decision makers even though they might have a keen interest to adopt blockchain technologies.

(c) Size of the respondent's company – big companies generally have more resources for evaluating new technology options and therefore could behave differently from smaller companies.

(d) Timing – data collection for this research spreads over a period of six months in order to collect sufficient samples. Respondents' views about adopting blockchain technologies may changed during this period of time.

Based on these considerations, the following remedial actions are taken.

(a) The TRA model is built based on the responses from "final decision makers" and those who are "taking major responsibility" for deciding whether to adopt blockchain technologies (see Table 3);

(b) In addition to (a), only include responses where company's annual revenue is in the range of USD 5-50M (see Table 3).

## 4.2 Result of Data Collection

A total of 263 valid questionnaires has been collected in the six-month period. With the criteria set-forth in Section 4.2, 117 responses satisfy the conditions and are being used for model development. In these 117 samples, 72.6% has an annual revenue between USD 5 to 25M, and the remaining 27.4% runs from USD 25 to 50M. In terms of business sector, 36.8% of the respondents come from manufacturing, 32.5% from trading, 10.3% from services sector, 15.4% from retail, and 5.1% belongs to other sectors. Regarding respondent's role, 34.2% claim to be final decision makers and 65.8% are, even though may not be the final decision maker, taking up major responsibilities for making decisions to adopt blockchain technologies.

For the remaining 146 samples not used for model development, 42 respondents have reported that they regularly involve in evaluating or investing in blockchain technologies. The rest 104 respondents mention that they are occasionally involved. This information would be used for analyzing model predictive power in section V.

# 5. DATA ANALYSES

Because of small sample size, it is infeasible to separately analyze data by business sector, revenue, or respondent's role. Therefore, the complete dataset is analyzed in a consolidated manner.

## 5.1 Cronbach' Alpha

Cronbach's Alpha test examines whether a construct can be vitally represented by the numerical average of the associated variables (i.e. respondent's answers range from 1 to 5). A Cronbach's Alpha higher than 0.7 indicate acceptable internal reliability [38]. For this survey, all Cronbach's Alphas are satisfactory (Table 4).

**Table 4. Cronbach's Alpha test**

| | No. of variables | No. of data | α |
|---|---|---|---|
| USF | 4 | 117 | 0.815 |
| EOU | 4 | 117 | 0.784 |
| TRD | 3 | 117 | 0.706 |
| NOR | 3 | 117 | 0.890 |
| ATT | 2 | 117 | 0.763 |
| INT | 2 | 117 | 0.830 |
| BHV | 2 | 117 | 0.918 |

## 5.2 Correlation and Discriminant Validity

Examining the independence of the constructs is especially important for this survey due to small sample size. In order for the model to be vital, one must determine whether the constructs are distinctive. That is, the theoretically uncorrelated constructs are actually uncorrelated. Researchers [39] have demonstrated that such discriminant validity can be claimed if

$$1 - r - SE > 0 \tag{1}$$

where r is the correlation coefficient
SE is the standard error

As shown in Table 5, discriminant validity is satisfied.

**Table 5. Discriminant Validity**

| Construct-pair | Correlation Coefficient (r) | Standard Error (SE) | 1 - r - 2*SE |
|---|---|---|---|
| USF - EOU | 0.523 | 0.075 | 0.327 |
| USF - TRD | 0.753 | 0.051 | 0.145 |
| USF - NOR | 0.749 | 0.074 | 0.103 |
| USF - ATT | 0.834 | 0.059 | 0.048 |
| USF - INT | 0.778 | 0.087 | 0.048 |
| USF - BHV | 0.746 | 0.095 | 0.064 |
| EOU - TRD | 0.552 | 0.069 | 0.310 |
| EOU - NOR | 0.671 | 0.088 | 0.153 |
| EOU - ATT | 0.555 | 0.095 | 0.255 |
| EOU - INT | 0.701 | 0.100 | 0.099 |
| EOU - BHV | 0.700 | 0.102 | 0.096 |
| TRD - NOR | 0.746 | 0.090 | 0.074 |
| TRD - ATT | 0.761 | 0.083 | 0.073 |
| TRD - INT | 0.627 | 0.124 | 0.125 |
| TRD - BHV | 0.554 | 0.134 | 0.178 |
| NOR - ATT | 0.792 | 0.054 | 0.100 |
| NOR - INT | 0.860 | 0.056 | 0.028 |
| NOR - BHV | 0.773 | 0.071 | 0.085 |
| ATT - INT | 0.783 | 0.072 | 0.073 |
| ATT - BHV | 0.680 | 0.086 | 0.148 |
| INT - BHV | 0.864 | 0.048 | 0.040 |

## 5.3 Mediation Test

Mediation test (Figure 2) verifies each proposed relation in the model via testing the hypotheses in Table 1.

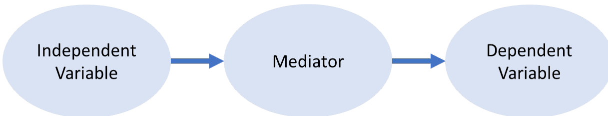


**Figure 2. Mediation test**

Mediation effect exists when the following three conditions are met [40, 41]:

(i) The independent variable significantly predicts the dependent variable;

(ii) The independent variable significantly predicts the mediator variable; and

(iii) When the dependent variable is regressed on both the mediator and the independent variable, the mediator significantly predicts the dependent variable while the predictive utility of the independent variable is reduced. The mediation is partial if both the mediator and the independent variable are significant. If the mediator is significant and the independent variable is becoming insignificant, this is a full mediation.

Results of mediation test (Table 6) support all the hypotheses in Table 1.

**Table 6. Mediation Test**

| Constructs | Correlation Coefficient | p-value | Mediation |
|---|---|---|---|
| USF - INT | 0.778 | 0.000 | Partial |
| USF - ATT | 0.834 | 0.000 | |
| USF - INT | 0.412 | 0.000 | |
| ATT | 0.440 | 0.000 | |
| EOU - INT | 0.701 | 0.000 | Partial |
| EOU - ATT | 0.555 | 0.000 | |
| EOU - INT | 0.385 | 0.000 | |
| ATT | 0.569 | 0.000 | |
| TRD - INT | 0.627 | 0.000 | Full |
| TRD - ATT | 0.761 | 0.000 | |
| TRD - INT | 0.075 | 0.406 | |
| ATT | 0.726 | 0.000 | |
| TRD - INT | 0.627 | 0.000 | Full |
| TRD - NOR | 0.746 | 0.000 | |
| TRD - INT | -0.033 | 0.644 | |
| NOR | 0.885 | 0.000 | |
| NOR - BHV | 0.773 | 0.000 | Full |
| NOR - INT | 0.860 | 0.000 | |
| NOR - BHV | 0.114 | 0.217 | |
| INT | 0.766 | 0.000 | |
| ATT - BHV | 0.703 | 0.000 | Full |
| ATT - INT | 0.809 | 0.000 | |
| ATT - BHV | 0.009 | 0.904 | |
| INT | 0.857 | 0.000 | |

## 5.4 Exploratory Analyses

Exploratory analyses are performed to explore further insights about the relationships among the variables. Significance levels are denoted by: * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$

(a) BHV is regressed against INT

**Table 7. BHV - INT**

| | Correlation Coefficient | p-value | $R^2$ |
|---|---|---|---|
| BHV - INT | 0.864 | 0.000 | 0.747 |

INT significantly predicts BHV, as suggested by the model.

(b) BHV is regressed against INT, ATT and NOR

**Table 8. BHV – INT, ATT, NOR**

| | | Correlation Coefficient | p-value | $R^2$ |
|---|---|---|---|---|
| BHV - | INT | 0.778 | 0.000 | 0.751 |
| | ATT | -0.030 | 0.713 | |
| | NOR | 0.128 | 0.202 | |

Although $R^2$ has increased by 0.004 when ATT and NOR are included, these constructs are non-significant predictors under the presence of INT. The observation is consistent with the proposed model.

(c) BHV is regressed against all other constructs

**Table 9. BHV – all other constructs**

| | | Correlation Coefficient | p-value | $R^2$ |
|---|---|---|---|---|
| BHV - | USF | 0.506 | 0.000 | 0.795 |
| | EOU | 0.335 | 0.001 | |
| | TRD | -0.286 | 0.039 | |
| | NOR | 0.165 | 0.174 | |
| | ATT | -0.158 | 0.172 | |
| | INT | 0.527 | 0.000 | |

$R^2$ has further increased by 0.044. Significant direct relationships BHV-USF and BHV-EOU exist.

(d) INT is regressed against ATT and NOR

**Table 10. INT – ATT, NOR**

| | | Correlation Coefficient | p-value | $R^2$ |
|---|---|---|---|---|
| INT - | ATT | 0.272 | 0.000 | 0.768 |
| | NOR | 0.645 | 0.000 | |

ATT and NOR significantly predict INT, as suggested by the model.

(e) NOR is regressed against USF, EOU and TRD

**Table 11. NOR – USF, EOU, TRD**

| | | Correlation Coefficient | p-value | $R^2$ |
|---|---|---|---|---|
| NOR - | USF | 0.424 | 0.000 | 0.705 |
| | EOU | 0.408 | 0.000 | |
| | TRD | 0.438 | 0.000 | |

In addition to the NOR-TRD relation suggested by the model, significant direct relationships NOR-USF and NOR-EOU also exist.

(f) ATT is regressed against USF, EOU and TRD

**Table 12. ATT - USF, EOU, TRD**

| | | Correlation Coefficient | p-value | $R^2$ |
|---|---|---|---|---|
| ATT - | USF | 0.661 | 0.000 | 0.863 |
| | EOU | 0.128 | 0.074 | |
| | TRD | 0.360 | 0.001 | |

Unlike the model suggests, the EOU is a non-significant predictor of ATT.

Based on the results of all the analyses and validations in this section, a revised model is proposed as in Figure 3. Besides a few additional relations have been identified, an interesting observation is perceived ease of use (EOU) does not significantly predict attitude to adopt (ATT). This contradicts the assumption of TAM. Other researchers [42-45] have also reported that EOU is not a significant predictor of ATT in their studies.

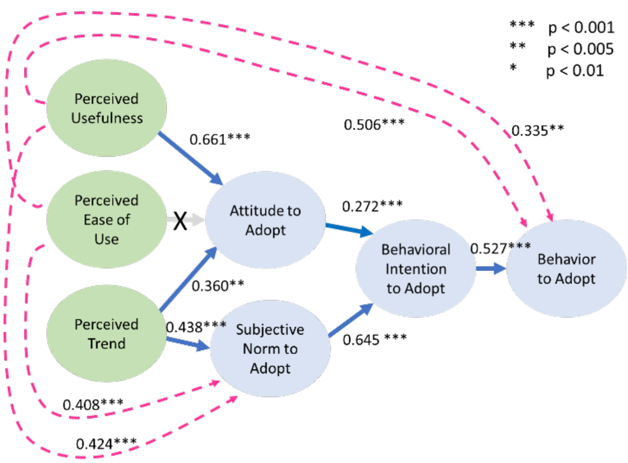


**Figure 3. Revised TRA model for blockchain technology adoption**

## 5.5 Predictive Power

The current model has been developed based on the responses from 117 decision makers who have control on whether to adopt blockchain technologies for their organization. To rigorously compare the effects of including responses from non-decision makers, additional models should be built. However, extensive efforts are required. Since USF, EOU and TRD are verified vital drivers, they are used for an indicative regression analysis.

By regressing BHV against USF, EOU and TRD, the constructs explain 70.2% variance of BHV. The high $R^2$ value confirms the model's predictive power on actual use of blockchain technologies.

If responses from non-decision makers are included, predictive power would be affected. With the same regression analysis, $R^2$ becomes 29.3% when the 42 respondents who claim to be regularly involved in evaluation / investing are included. When all responses are used for regression, $R^2$ becomes 18.2%. Hence, models based on non-segmented data would not be reliable for predicting actual use. The deterioration of $R^2$ reflects that, in an organization setting, non-decision makers may be forced to use or not to use the technologies regardless of his or her intention to use.

To further verify this view, INT is regressed against USF, EOU and TRD for the above three situations. Results are shown in Table 13.

**Table 13. Indicative Predictive Power Comparison**

| $R^2$ | Model 1 (N=117) | Model 2 (N=159) | Model 3 (N=263) |
|---|---|---|---|
| | Decision makers only | Decision makers and those with regular involvement | All respondents |
| Behavior to adopt (BHV) | 70.2% | 29.3% | 18.2% |
| Behavioral intention to adopt (INT) | 72.6% | 73.0% | 65.3% |

As more responses are included, predictive power for intention remains high in all cases. Hence, user's inability to make final adoption decision would not affect the predictive power on INT but would seriously impact the predictive power on BHV. The observation reaffirms other researchers queries about the connection between attitude of using and actual use [10-19]. Results of this study is consistent with meta-analysis in [46].

# 6. DISCUSSIONS AND CONCLUSIONS

## 6.1 General Observations

The revised model in Figure 3 provides quantitative measurements about the relative importance of the drivers. As some other researches have also demonstrated, perceived ease of use (EOU) is not a significant predictor of attitude to adoption (ATT) in this study. This contradicts the assumption of TAM. It is also of interest to see that the weight of subjective norm (NOR) is considerably higher than attitude (ATT). This phenomenon is similar to the observations in smoking cessation campaigns mentioned in Section II. With the insights gained from TRA model, more focused business development strategies can be derived.

## 6.2 Limitations

This research has illustrated a practical and systematic way to understand the drivers for actual blockchain technology adoption. Instead of developing complex models, predictive power is enhanced by data segmentation at the outset.

The model has been kept as simple as feasible in order to suit practitioners need. Section IV has discussed some limitations of this approach. It is particular important to realize that this research is not sector specific due to practical data collection constraints. Since every sector may have remarkably different behavior, separated investigations are crucial for accurate sectoral strategy development.

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