

## **An empirical assessment of the determinants of Blockchain implementation in the food industry**

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### **1. INTRODUCTION**

The food supply chain (FSC) is critical for producing and distributing food products to sustain human life. Fundamentally, FSC consists of various stages related to transiting and transporting food from the point of production to final consumption or disposal (Barbosa, 2021). FSC possesses specific characteristics and unique challenges that distinguish them from others such as manufacturing. Particularly, food products are perishable, heavily subjected to price volatility and climate conditions, and suffer serious wastage and security issues (Barbosa, 2021). To overcome these critical and persistent challenges, FSC stakeholders have been exploring advanced technologies as potential remedies. Amid the emergence of Industry 4.0., among several technologies, Blockchain is considered one of the key innovations that can bring valuable transformation to agriculture/food sector (Rana et al., 2021). Whilst FSC is among the first to explore the potential of Blockchain, the majority of the projects remain at a conceptual or pilot stage (Vu et al., 2021). Thus, there is still a strong need for research looking at the adoption process of Blockchain, especially in a specific industry setting (Wamba and Queiroz, 2020), such as the FSC.

While Blockchain is considered a disruptive technology, adopting technological innovation in the SCM domain is not a new phenomenon. In the past, several transformative technologies have emerged for better SCM as RFID (Reyes et al., 2016), or big data analytics (Kache and Seuring, 2017). When studying the adoption of technological innovation, Innovation Adoption (IA) theories have been commonly used in the extant literature. In a broad sense, IA perspectives theorize and explain why and how an innovation (i.e., a product, a process, or a technology), that is new to the adopting units (i.e., organizations or individuals) is introduced, developed, adopted, and implemented (Pichlak, 2015). Prominent IA theories and concepts have been used to a great extent to study the adoption of technologies such as RFID (Hossain et al., 2016; Reyes et al., 2016), and Blockchain in a generic SCM setting (Wamba and Queiroz, 2020). Thus, it can be seen that IA is a suitable approach to understanding the Blockchain integration process in the specific context of FSC.

As discussed previously, there is an evident need for researching the implementation of Blockchain for organizations. Early attempts at exploring this topic have been made in the extant literature, as many studies investigated the antecedents of the decision to adopt Blockchain (For example see Wong et al. (2020) and Queiroz et al. (2020)). It is, however, observed that less effort has been put into studying the journey by which Blockchain gets integrated into an organization. Studying this particular aspect could uncover valuable insights that lead to a smooth and successful implementation of Blockchain technology for companies, creating business values (Pichlak, 2015). To address this gap in the current literature, this study investigates the Blockchain implementation process and its associated determinants, in the specific setting of FSC. Drawing from prominent theoretical lenses of IA, namely the Diffusion of Innovation (DOI) (Rogers, 2003), the Technology – Organization – Environment framework (TOE) (Tornatzky et al., 1990), and other established models, this study first developed a multi-stage model to capture different phases of Blockchain adoption and their determinants. Sixteen hypotheses were developed about the key relationships between primary determinants and adoption phases. Then, quantitative data was collected using surveys to statistically test and validate the model to uncover, what the key influential factors to each of the adoption stages are in the

specific context of FSC. The testing the hypotheses show that influential factors can have different influences, depending on the phase of the adoption. Therefore, it can provide a useful reference for practitioners in the field when adopting Blockchain, especially when the technology is still at the embryonic stage of the development.

## 2. THE RESEARCH MODEL AND DEVELOPMENT OF HYPOTHESES

There are two main streams of research in the IA literature: a dichotomy of the process approach and a factor approach (Pichlak, 2015). The latter focuses on influential factors that constitute the decision to adopt a new technological innovation, meanwhile the former examines the process by which a technology gets integrated into an organization. As the aim of this study is to explore the course of Blockchain diffusion in FSC organizations, it is more aligned with the second stream of IA research. Prior to this study, the authors conducted a systematic literature review on the topic of Blockchain usage and adoption in the FSC (Vu et al., 2021). The result is a conceptual model with FSC pertinent determinants of the adoption process. Inspired by the prior work, this study's research model (Figure 1) proposes three distinct phases of the Blockchain implementation at the organizational level, which are Initiation (INI) – where an organization explores the potential and suitability of Blockchain, Adoption (ADOP) – where the final decision of adopting Blockchain is made and organization details the plan to integrate the technology, and Implementation (IMPL) – where the organization takes necessary steps to fully deploy the technology. Further, four clusters of main determinants of the implementation process are identified as technology, organization, environment, and managers' characteristics.

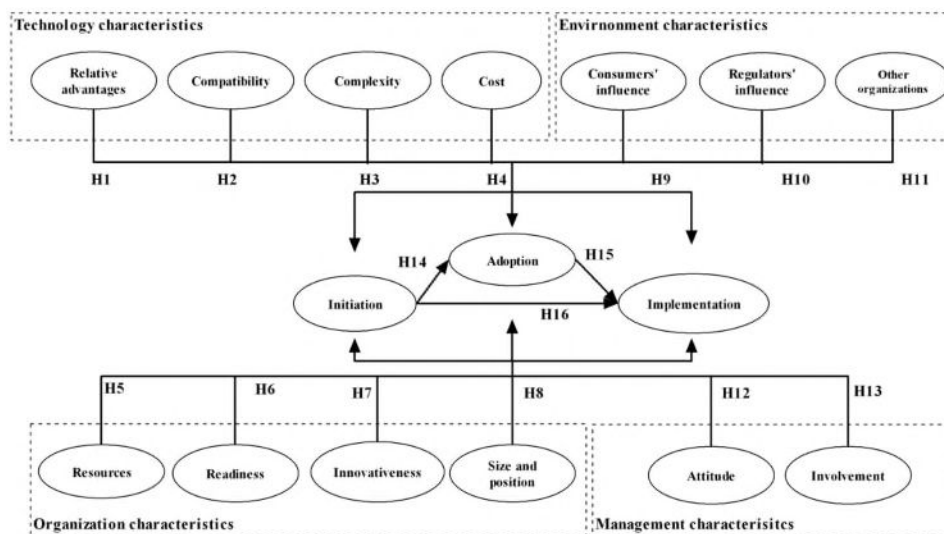


Figure 1. The research model for Blockchain implementation in FSC.

For the technology context, extant literature has identified that firms in FSC are motivated to adopt Blockchain due to the potential advantages it could bring (e.g. reliable information sharing, better provenance of food); and to implement the technology firms need to be aware of the compatibility and complexity of Blockchain (Zhao et al., 2019; Vu et al., 2021). These insights are consistent with what DOI suggested (Rogers, 2003), and furthermore, the cost is also suggested as an important factor in the adoption of Blockchain (van Hoek, 2019). On the other hand, the TOE framework proposed that certain characteristics of the organization, such as size, structure, culture, etc. are influential to the process of implementing an innovation (Tornatzky et al., 1990). In the food industry, the size and position of a company are found to be relevant to the adoption of Blockchain, as large enterprises tend to have sufficient resources and technological know-how (Vu et al., 2021). Subsequently, resources and readiness (i.e. being capable to implement

complex technology) are also considered important when adopting technological innovation (Pichlak, 2015; Wamba and Queiroz, 2020). Last but not least, organizations need to possess a certain level of innovativeness to initiate a Blockchain project, as the technology is still considered novel for the field of FSC (Vu et al., 2021). Environment context refers to influential factors of the implementation process that are outside of the adopting organization setting. Extant literature about Blockchain for FSC highlights that other organizations within the FSC, consumers, and regulators can influence the decision of adopting Blockchain, as they increasingly demand more trustworthy information about the provenance and authenticity of food products (Zhao et al., 2019; Vu et al., 2021). Similarly, managers' characteristics are critical to the adoption of new technology, as suggested by past models of the IA process (Pichlak, 2015; Reyes, et al., 2016) and studies looking at Blockchain use in SCM (van Hoek, 2019). Drawing from pertinent literature and established models of the technology adoption process, following hypotheses are established:

*H1: Blockchain's relative advantages (RA) are positively related to Blockchain initiation, adoption, and implementation.*

*H2: Blockchain's compatibility (CPA) is positively related to Blockchain initiation, adoption, and implementation.*

*H3: Blockchain's complexity (CPX) is positively related to Blockchain initiation, adoption, and implementation.*

*H4: Blockchain's cost (CST) is positively related to Blockchain initiation, adoption, and implementation.*

*H5: Organization size and position (SAP) is positively related to Blockchain initiation, adoption, and implementation.*

*H6: Organization's readiness (READ) is positively related to Blockchain initiation, adoption, and implementation.*

*H7: Organization's resources (RESO) are positively related to Blockchain initiation, adoption, and implementation.*

*H8: Organization's innovativeness (INOV) is positively related to Blockchain initiation, adoption, and implementation.*

*H9: The influence of consumers (CONIN) has a positive influence on Blockchain initiation, adoption, and implementation.*

*H10: The Influence of regulators (REGIN) has a positive influence on Blockchain initiation, adoption, and implementation.*

*H11: The influence of other organizations (ORGIN) has a positive influence on Blockchain initiation, adoption, and implementation.*

*H12: Managers' attitude (ATT) toward Blockchain has a positive influence on Blockchain initiation, adoption, and implementation.*

*H13: Managers' involvement (INVOL) in the projects has a positive influence on Blockchain initiation, adoption, and implementation.*

*H14: The Initiation stage positively influences the adoption stage.*

*H15: The Adoption stage positively influences the implementation stage.*

*H16: The Initiation stage positively influences the implementation stage.*

### **3. RESEARCH METHODOLOGY**

Quantitative data gathered following questionnaire survey, is utilized to test the proposed hypotheses and analyze the implementation stages. This is a common method in studying the adoption process of technology (Hossain et al., 2016; Wamba and Queiroz, 2020; Wong et al., 2020). Before the distribution of the survey, the authors had multiple rounds of discussions within the research team to formulate the questionnaires. Further, a pilot round was conducted with 15 industry experts to validate the relevance and the clarity of the questions. The final version of the survey was used to collect the data from the individuals working in the UK food industry. To make sure the respondents of the survey

had the appropriate expertise regarding implementing Blockchain, a set of screening questions were used at the beginning and unqualified candidates were not able to take part in the survey. At the end of this process, 159 responses were collected. Moreover, Partial Least Square – Structural Equation Modelling (PLS-SEM) was chosen as the analytical approach to analyze the results and test the model. PLS-SEM is a strong method for an exploratory study, where researchers want to extend current theoretical foundations to understand a developing area (Hair *et al.*, 2019). Particularly for this case, the authors aim to elaborate on established IA theories and concepts to explain a new phenomenon – the adoption of Blockchain in the FSC domain. A basic guideline for selecting a sample size is that it should be at least equal to the number of structural paths directed at a single construct (indicated by the arrows in the model) (Hair *et al.*, 2012). In this case, IMPL has the largest number of 15 structural paths connecting to it, thus a sample of at least 150 is required for testing this model.

#### 4. RESULTS AND ANALYSIS

In this section, the analysis results of the research model with the survey data are presented. Two main sections of the model are assessed: the measurement model, and the structural model. The measurement model, sometimes referred to as the outer model, includes the indicators of a construct (Hair *et al.*, 2019). In another word, the assessment of the measurement model indicates whether a construct (e.g. Relative advantage – RA) is reliably and validly measured by its indicators- the measurement items. Each measurement item of a construct is captured by one question in the survey, where a Likert scale of 1 to 5 (with one being strongly disagree and five being strongly agree) was applied. Due to the limited length of this conference paper, the full questionnaire is not included, and could be provided as a supplementary document upon request.

| Construct | CR    | AVE   | MI     | Loading | p-value for MI |
|-----------|-------|-------|--------|---------|----------------|
| RA        | 0.831 | 0.713 | RA1    | 0.767   | 0.001          |
|           |       |       | RA2    | 0.915   | 0              |
| CPA       | 0.818 | 0.697 | CPA1   | 0.943   | 0              |
|           |       |       | CPA2   | 0.71    | 0.001          |
| CPX       | 0.8   | 0.575 | CPX1   | 0.858   | 0              |
|           |       |       | CPX2   | 0.755   | 0.001          |
|           |       |       | CPX3   | 0.646   | 0.014          |
| CST       | 0.875 | 0.779 | CST1   | 0.953   | 0              |
|           |       |       | CST2   | 0.806   | 0.003          |
| RESO      | 1     | 1     | RESO2  | 1       |                |
| READ      | 0.86  | 0.755 | READ1  | 0.834   | 0.001          |
|           |       |       | READ2  | 0.902   | 0              |
| INOV      | 0.888 | 0.798 | INOV1  | 0.895   | 0              |
|           |       |       | INOV2  | 0.891   | 0              |
| SAP       | 1     | 1     | SAP1   | 1       |                |
| CONIN     | 0.825 | 0.707 | CONIN1 | 0.688   | 0.02           |
|           |       |       | CONIN2 | 0.97    | 0.001          |
| ORGIN     | 1     | 1     | ORGIN3 | 1       |                |
| REGIN     | 1     | 1     | REGIN2 | 1       |                |
| ATT       | 0.848 | 0.738 | ATT1   | 0.928   | 0              |
|           |       |       | ATT2   | 0.784   | 0.002          |
| INVOL     | 0.857 | 0.751 | INVOL1 | 0.828   | 0              |
|           |       |       | INVOL2 | 0.903   | 0              |
| INI       | 0.815 | 0.688 | INI1   | 0.861   | 0              |
|           |       |       | INI2   | 0.797   | 0              |
| ADOP      | 0.752 | 0.604 | ADOP1  | 0.719   | 0              |
|           |       |       | ADOP2  | 0.832   | 0              |
| IMPL      | 0.739 | 0.486 | IMPL1  | 0.698   | 0              |
|           |       |       | IMPL2  | 0.655   | 0              |
|           |       |       | IMPL3  | 0.736   | 0              |

Table 1. Loadings of measurement items and average variance extracted (AVE) and composite reliability (CR) of the constructs.

To assess the validity of the measurement items (MI), the loadings value of each item is utilized. The outer loading of each MI first needs to be statistically significant, and further should be at least moderately strong (no less than 0.4 according to Hair et al. (2012)). The initial calculation of the model thus excluded SAP2, ORGIN1, ORGIN2, RESO1, and REGIN1 due to insufficient loadings value and p-value. As seen in Table 1, the rest of the MI are statistically significant and have strong loading values, indicating that they effectively measure the corresponding constructs (a measured-by-single-item construct always has the loading of 1). To test the reliability of the MI in measuring the constructs, a CR score is used. A higher value of CR indicates a higher level of internal consistency reliability of the indicators for measuring the construct, and a value of 0.6 or higher is acceptable in exploratory research (Hair et al., 2019).

As presented in Table 2, all constructs are reliably measured by their MI, with CR scores of at least 0.7. Constructs that are measured by a single indicator always have a CR score of 1. At the construct level, AVE is used to assess the convergent validity of the constructs. An AVE value of 0.5 or higher implies that the construct, on average, "explains more than half of the variance of the indicators" (Hair et al., 2012, p. 115). The majority of the constructs are qualified with this test. The exception is IMPL, which has an AVE value of .486, and since this is not significantly less than the 0.5 thresholds, this can be considered acceptable. Last but not least, discriminant validity, the extent to which a construct differs from others in an empirical sense (Hair et al., 2012), is evaluated for the constructs by the Fornell-Larker criterion approach. The results, as seen in Table 2, imply that a construct shared more variance with its associated indicators than with any other construct, thus discriminant validity is not an issue with this study.

|       | ADOP         | ATT          | CONIN        | CPA          | CPX          | CST          | IMPL         | INI          | INOV         | INVOL        | ORGIN    | RA           | READ         | REGIN    | RESO     | SAP      |
|-------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|----------|--------------|--------------|----------|----------|----------|
| ADOP  | <b>0.777</b> |              |              |              |              |              |              |              |              |              |          |              |              |          |          |          |
| ATT   | -0.134       | <b>0.859</b> |              |              |              |              |              |              |              |              |          |              |              |          |          |          |
| CONIN | -0.079       | 0.469        | <b>0.841</b> |              |              |              |              |              |              |              |          |              |              |          |          |          |
| CPA   | -0.052       | 0.466        | 0.444        | <b>0.835</b> |              |              |              |              |              |              |          |              |              |          |          |          |
| CPX   | -0.203       | 0.018        | 0.068        | 0.045        | <b>0.758</b> |              |              |              |              |              |          |              |              |          |          |          |
| CST   | -0.119       | 0.238        | 0.099        | 0.052        | 0.457        | <b>0.882</b> |              |              |              |              |          |              |              |          |          |          |
| IMPL  | 0.505        | -0.014       | 0.004        | 0.173        | -0.121       | -0.093       | <b>0.697</b> |              |              |              |          |              |              |          |          |          |
| INI   | 0.43         | -0.075       | -0.083       | -0.012       | -0.046       | -0.05        | 0.471        | <b>0.829</b> |              |              |          |              |              |          |          |          |
| INOV  | -0.082       | 0.575        | 0.49         | 0.581        | -0.026       | 0.217        | 0.022        | -0.1         | <b>0.893</b> |              |          |              |              |          |          |          |
| INVOL | -0.021       | 0.566        | 0.443        | 0.496        | -0.021       | 0.151        | 0.107        | -0.148       | 0.563        | <b>0.866</b> |          |              |              |          |          |          |
| ORGIN | -0.159       | 0.23         | 0.394        | 0.227        | 0.302        | 0.223        | -0.086       | -0.132       | 0.225        | 0.281        | <b>1</b> |              |              |          |          |          |
| RA    | 0.15         | 0.18         | 0.281        | 0.48         | 0.101        | 0.008        | 0.085        | 0.038        | 0.391        | 0.337        | 0.187    | <b>0.844</b> |              |          |          |          |
| READ  | -0.118       | 0.574        | 0.478        | 0.382        | 0.111        | 0.238        | -0.038       | -0.077       | 0.579        | 0.426        | 0.321    | 0.252        | <b>0.869</b> |          |          |          |
| REGIN | -0.056       | 0.374        | 0.338        | 0.293        | 0.075        | 0.078        | -0.156       | -0.136       | 0.394        | 0.304        | 0.164    | 0.267        | 0.33         | <b>1</b> |          |          |
| RESO  | -0.064       | 0.32         | 0.412        | 0.477        | -0.047       | 0.023        | -0.022       | -0.038       | 0.51         | 0.434        | 0.14     | 0.438        | 0.291        | 0.43     | <b>1</b> |          |
| SAP   | -0.014       | 0.294        | 0.355        | 0.45         | -0.055       | 0.029        | 0.075        | 0.069        | 0.422        | 0.299        | 0.268    | 0.244        | 0.349        | 0.287    | 0.425    | <b>1</b> |

Table 2. Fornell-Larcker criterion for all constructs.

Subsequently, the structural model, also known as the inner model is assessed. Before the path coefficient of the main relationships between exogenous and endogenous variables, and their p-value, are evaluated. Hair et al (2019) recommended checking for collinearity issue (high level of correlations between predictor constructs) of the inner model using the variance inflation factor (VIF). VIF value for the inner path is considered satisfactory with a value less than 3. As indicated in Table 3, collinearity is not an issue for this study.

|      | ADOP  | ATT   | CONIN | CPA   | CPX   | CST   | INI   | INOV  | INVOL | ORGIN | RA    | READ  | REGIN | RESO  | SAP   |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| ADOP |       | 2.154 | 1.733 | 2.045 | 1.493 | 1.465 | 1.09  | 2.537 | 1.904 | 1.426 | 1.525 | 1.911 | 1.408 | 1.811 | 1.519 |
| IMPL | 1.414 | 2.179 | 1.734 | 2.054 | 1.552 | 1.467 | 1.333 | 2.539 | 1.937 | 1.433 | 1.607 | 1.914 | 1.415 | 1.844 | 1.519 |
| INI  |       | 2.149 | 1.733 | 2.044 | 1.493 | 1.465 |       | 2.524 | 1.877 | 1.407 | 1.506 | 1.911 | 1.387 | 1.811 | 1.486 |

Table 3. VIF value for the structural path.

Figure 2 provides a holistic view of the assessment of the structural model, together with the loading value of the reflective indicators for their associated constructs. A bootstrapping procedure was carried out to estimate the path coefficients of the structural model and the significance levels.

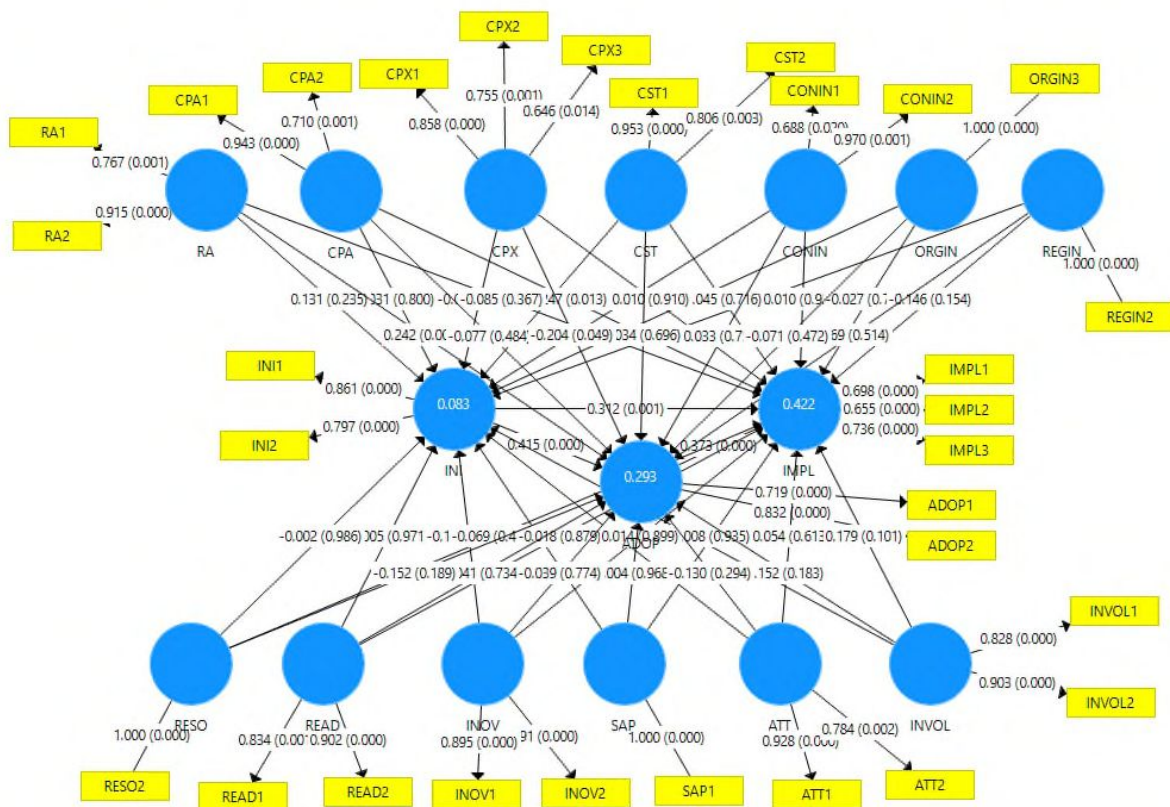


Figure 2. Research model with bootstrapping results.

A sizable and significant relationships between the main constructs, as the results of evaluating the research model are reported in Table 4. Generally for exploratory research such as this study, researchers can assume a confidence level of 10% (Hair et al., 2012). Thus, the p-value is utilized to assess the significance level of the relationships between endogenous and exogenous constructs of this study's research model. When assuming a significance level of 10%, the p-value must be smaller than 0.1 to indicate that a relationship is statistically significant. According to Table 4, the significant relationships concluded from statistical tests range from not very strong (approximately 0.17 to 0.18 of path coefficient value) to moderately strong (close to or more than 0.4 of path coefficient value).

| Hypothesis | Relationships | Path coefficient | P-value | Testing  |
|------------|---------------|------------------|---------|----------|
| H15        | ADOP -> IMPL  | 0.373            | 0       | Accepted |
| H14        | INI -> ADOP   | 0.415            | 0       | Accepted |

|      |               |        |       |          |
|------|---------------|--------|-------|----------|
| H16  | INI -> IMPL   | 0.312  | 0.001 | Accepted |
| H1b  | RA -> ADOP    | 0.242  | 0.012 | Accepted |
| H2c  | CPA -> IMPL   | 0.247  | 0.015 | Accepted |
| H3b  | CPX -> ADOP   | -0.204 | 0.047 | Accepted |
| H5a  | SAP -> INI    | 0.174  | 0.079 | Accepted |
| H13c | INVOL -> IMPL | 0.179  | 0.093 | Accepted |

Table4. Path coefficients.

Finally, the coefficient of determination ( $R^2$  value) is evaluated. This is an important, and commonly used measurement for the predictive power of the model.  $R^2$  represents the amount of variance in the dependent constructs explained by all of the independent constructs associated with it (Hair et al., 2019). In this case,  $R^2$  is calculated for the three constructs representing the three stages of adoption: INI, ADOP, and IMPL. The respective values of their  $R^2$  are 0.083, 0.293, and 0.422 (as seen in Figure 2). Thus, it can be concluded that, in terms of predictive accuracy, the research model proposed in this study has a moderate level of accuracy when predicting ADOP and IMPL, and a weak level of accuracy when capturing INI.

## 5. DISCUSSION AND CONCLUSION

In this study, a three-stage model for the implementation of Blockchain in the setting of FSC is developed and validated following the assessment of the empirical data. The objective of this study is to examine the implementation process of Blockchain for organizations in the food industry, and more importantly, to assess the impacts of prominent determinants on different stages of implementation. As indicated by extant IA literature, during the process of integrating a new technological innovation into an organization, there could be various influential factors that either advance or hinder such a process. By using empirical data collected from experts in the food industry (with relevant experience in deploying Blockchain), this study aims to specifically uncover pertinent contextual determinants to the integration of the technology in the FSC setting.

As indicated by the results discussed in Section 4, the initiation stage has a strong positive influence on the adoption and implementation stage, and the adoption stage has a strong positive influence on the implementation stage. This suggests to practitioners that the three phases of implementation (initiation, adoption, and implementation) sufficiently represent the actual process of integrating Blockchain, and more importantly, the success and efficiency of each stage has a strong impact on the results of the following stage. For instance, a good understanding of Blockchain, combined with a well-defined scope of the Blockchain project, set the adopting unit up for successful adoption and later implementation of the technology in the whole organization. The findings of this study also suggest that the size and position of a company positively influence the initiation stage of implementing Blockchain. This is consistent with what the literature suggested, as large enterprises in the FSC have the necessary drive, resources, and capabilities to initiate Blockchain projects (Vu et al., 2021). It is also observed that the relative advantages that Blockchain could bring to the adopting unit have a positive impact on the decision of using the technology and on the contrary, the complexity of Blockchain is a major hindrance to its adoption. Finally, the compatibility of Blockchain – implying the degree to which the capability of the technology aligns with the needs of the organization and how easy it is to integrate Blockchain with the existing IT infrastructure of the adopting unit – is important to the success of the implementation stage. This is understandable, as, in the final stage of adoption, the organization looks to fully incorporate Blockchain into its structure, thus the compatibility of the technology is very important for a smooth deployment process. Further, the involvement of top management during the implementation stage has a positive influence on the success of this stage, signifying the important roles of managers during the process of implementing Blockchain.

This study also has certain limitations leading to future research directions. As the study is grounded strictly in the context of FSC, generalization of the results to other settings must be done with care. Therefore, future studies could apply this model in different setting (e.g. pharmaceutical or auto-manufacturing supply chain) to contribute to a holistic understanding of Blockchain adoption. Further, as Blockchain is still a developing technology in the field of FSCM, thus, some respondents' understanding of Blockchain could be insufficient. In-depth case studies of successful Blockchain adoption in the future thus can help to validate the results of this study.

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