ASSESSING THE IMPACT OF ABSORPTIVE CAPACITY RISK ON INDUSTRY-UNIVERSITY COLLABORATION PERFORMANCE USING STRUCTURAL EQUATION MODELLING

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ABSTRACT

Industry-University collaborations offer means through which tech industries can have access to external ideas and resources to meet the ever changing market needs. However, many tech industries find it difficult to establish thriving collaborations. Therefore, to fully reap the benefits of Industry-University collaborations, risks need to be managed upfront through identifying them, assessing their likelihood, possible impact, and devising an overall action plan to mitigate them.

The present work contributes to industry-university collaboration research by conducting a quantitative evaluation, in the context of Botswana high-tech Industry. The main research question is; do Absorptive Capacity risks negatively influence Industry-University Performance in the context of Botswana tech Industries?

Hypotheses were tested through the application of Structural Equation Modelling (SEM), based on partial least squares (PLS) approach and the support of the SmartPLS 3.0 software. An electronic survey questionnaire was distributed to Botswana high- tech Facebook pages and a total of 96 usable responses were collected. Several Absorptive capacity risks were assessed and, only Acquisition Risk was found to negatively influence Industry-University Performance in the Botswana high tech industry.

The research is envisioned to help high tech industry managers in Botswana to proactively pay attention to acquisition risks and mitigate them when collaborating with universities.

Keywords: *Industry-University Collaboration; Collaboration Risks; Industry-University Performance, Risk Assessment, PLS-Structural equation Modeling*

INTRODUCTION

The ever increasing global competition and the need to meet the fluctuating market demands has pushed technology firms to optimize their innovative capability. Access to strategic resources is a great source of competitive edge (Lütjen *et al.*, 2019). However, sometimes the vital resources required to produce innovative products/services exist outside the boundaries of the organisations (Paranhos, Perin and Mercadante, 2019). Therefore technology firms are progressively collaborating with universities to have access to a pool of complementary resources they may internally. This is designated as Industry-University collaboration (IUC) (Ungureanu, Bertolotti and Macri, 2018), (Brunswicker and Chesbrough, 2018).

IUCs provide a myriad benefits such as cost sharing, shorter product lifecycle and risk sharing (Cheng and Chen, 2010). To fully reap these benefits of turbulent and complex IUCs, technology firms need to possess high levels of absorptive capacity (ACAP) (Yang and Tsai, 2019). ACAP is defined as a firm's capability to assimilate, transform and exploit the acquired resources to facilitate the innovation process (Aliasghar *et al*., 2019).

High levels of ACAP is an exceptional source of competitive edge for firms. It allows them to spot new opportunities and threats, which consequently help them develop new processes of innovating (Hurmelinna-laukkanen, 2012). On the other hand, low levels of ACAP can deter the success of IUCs. Therefore determining a firm's ACAP level is imperative. However, no previous work has studied the depth of how ACAP risks affects IUC performance in Botswana. A significant number of IUCs fail for a wide range of reasons that vary considerably with each industry, region, or country (Alexander, Miller and Fielding, 2015). Therefore they must be assessed separately.

In this light, the present paper conducts a quantitative evaluation of the ACAP risks on IUC performance in the context of Botswana high-tech Industry. This is achieved by the application of Structural Equation Modelling (SEM), based on partial least squares (PLS) approach. The main research question is; do ACAP risks negatively influence IUC's in the context of Botswana high tech industries? The study is envisioned to help devise risk strategies to prevent probable adverse effects on IUC performance in Botswana.

MOTIVATION FOR TECHNOLOGY INDUSTRIES ENGAGEMENT IN IUCS

Initially technology industries embraced the process of generating ideas and turning inventions into commercialized products or services, internally with minimal interaction with external parties. However, this closed innovation model is fraught with many challenges that hinder innovation success (Chesbrough, 2003b). For example, the research and development (R&D) necessary for developing products and services is lengthy, costly, and risky (Al-ashaab, Flores and Magyar, 2011), (Öberg and Alexander, 2019). Therefore, it is becoming more problematic for technology industries to innovate in short periods of time, solely based on their internal capabilities (Vrande, Jong and Vanhaverbeke, 2009).

Technology industries are shifting from the conventional closed innovation model to engaging with communities that comprise numerous actors in interactive relationships (Brunswicker and Chesbrough, 2018), (Pekkola and Ukko, 2015), (Badillo, 2017), (Ombrosi, Casprini and Piccaluga, 2018). This notion is referred to as open innovation (OI) and it was coined by Chesbrough. OI encourages firms to tap on both the internal and external knowledge and resources to optimize their innovation activities (Chesbrough, 2003a), (Abouzeedan and Hedner, 2012).

One variation of OI is through **external networking with external universities** (Ungureanu, Bertolotti and Macri, 2018)**.** This is designated as industry-university collaboration (IUC). IUCs offer a means through which technology industries can exchange ideas and share resources with external partners to meet market demands (Fei-yu, Chong and Wei-ning, 2014), (Parida and Cedergren, 2016). Industries that collaborate with universities hold competitive edge due to access to diverse specialized human capital and advanced infrastructure (Savitskaya, Salmi and Torkkeli, 2010), (Zhang, Hui, Wang, He-Cheng, Zhou, 2015), (Song, Zhu and Lv, 2016), (Aliasghar, Rose and Chetty, 2019). They can also enhance the innovation speed by splitting labour among partners.

RESOURCE BASED VIEW

Not all industries engaging in collaborations with universities are successful (Cheng *et al.*, 2013), (Baker, Kan and Teo, 2011). Owing to the fact that industry and universities have varying objectives, working habits, cultures and experience different constraints (Rybnicek and Königsgruber, 2019)**,** (Yilmaz, Won and Seok, 2017) (Hitchen *et al.*, 2017). Additionally, the involved actors are constantly evolving, making the relationship complex and prone to failure (Wei *et al.*, 2019). In their work, (Bidault and Castello, 2010) discovered that approximately 50-80% of ‘‘co-innovation’’ projects end up in failure. Therefore all these factors need to be managed strategically.

The **resource-based view (RBV)** theory posits that access to strategic resources is a chief antecedent of an organization’s competitive advantage (Lütjen *et al.*, 2019). However, these resources do not necessarily have to exist inside the confines of an organization (Paranhos, Perin and Mercadante, 2019) (Panda and Reddy, 2016) . Therefore, technology firms, engage in collaborative innovation with universities to access complementary resources that may be deficient inside the firm. The benefits of these collaborations only become possible to achieve when a firm has the capacity to identify and capitalize on the acquired resources (Parida and Cedergren, 2016). Thus justifying ACAP’s relevance in IUCs.

THEORETICAL FRAMEWORK

ACAP affords organizations to the luxury to effectively identify new opportunities and threats. Thus, subsequently helping them develop new processes for the advancement of the innovation tasks (Hurmelinna-laukkanenb, 2012). On the contrary, absence of ACAP can be detrimental to the performance of IUCs. It can hinder firms from exploiting and embedding new knowledge from IUCs. Firms that are unable to embed new knowledge are unable to innovate (Wu and Chen, 2014), (Parida and Cedergren, 2016), (Sağ, Sezen and Güzel, 2016).

Therefore ACAP risk must be assessed beforehand in order to develop action plans to help mitigate possible impact that may rise as a result of low levels of ACAP. Essentially, ACAP risk is conceptualized in four basic constructs. Acquisition risk, assimilation risk, transformation risk and exploitation risk (Aliasghar et al., 2019).

Acquisition risk depicts a firm's inability to scan and acquire external knowledge from sources outside the boundaries of the firm. They also lack the ability to identify relevant collaborative partners and not well versed with laws and regulations surrounding partnerships (Lütjen *et al.*, 2019). A firm with a low acquisition capability fails to continuously gather, filter, and scrutinize technologies and market opportunities (Flatten, 2011). *Therefore this paper hypothesizes that;*

H1: Acquisition risk is negatively related to IUC performance.

Assimilation risk signals a firm's inability to prepare routines necessary for dissecting and interpreting the externally obtained knowledge. Firms with low levels of assimilation ACAP lack the capacity to communicate ideas across all concerned parties. Additionally, fail to devise incentives for maintaining a high level of interaction with external actors by (Sharma and Martin, 2018). *Therefore this paper hypothesizes that;*

H2: Assimilation risk is negatively related to IUC performance.

Transformation risk denotes the inability to refine routines that foster the integration of existing knowledge with newly sourced and assimilated knowledge. Firms with low transformation ACAP are unable to structure and use sourced knowledge from IUCs. *Therefore this paper hypothesizes that;*

H3: Transformation risk is negatively related to IUC performance.

Lastly, **exploitation risk** signals a firm's inability to adjust, advance and utilize its routines, technologies, and proficiencies to develop new products or services based on the transformed knowledge (Flatten, 2011). Firms facing exploitation risk fail to realign certain assets, re-assess strategies and incorporating necessary alterations for better utilization of the externally sourced help (Aliasghar, Rose and Chetty, 2019). *Therefore this paper hypothesizes that;*

H4: Exploitation risk is negatively related to IUC performance.

Based on the hypothesis above, the author proposed a framework as shown in Figure 1 to exhibit the correlations among the constructs that are being investigated.

INDUSTRY-UNIVERSITY COLLABORATION PERFORMANCE

Firms' motives to engage in IUCs are usually informed by the generic outcomes such as increased knowledge base, access to infrastructure, specialized labor and so forth (Benhayoun *et al.*, 2020). However, a primary hiccup for management is how to assess these collaborations via hard performance metrics, since it is challenging to make a quantitative case for participation in IUCs.

Both the universities, and industry are interested in fruitful collaborations that offer mutual benefits to the involved parties (Yang and Tsai, 2019). Therefore, identifying proper indicators is essential to track the effects of interactions between industries and universities over time. This assists in making adjustment and improvements if necessary. This is further broken down in the methodology section.

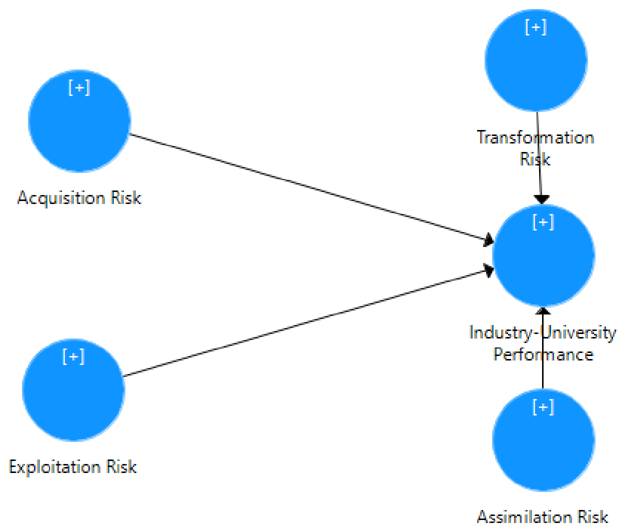

Figure 1 Proposed Framework for assessing the impact of ACAP risk on IUC performance

Methodology

This section discusses the procedures for collecting the data in order to answer the research question and test hypothesis of the paper. The topics to be discussed in this section include the research design, participants, data collection methods, research instrument, and data modelling techniques and analysis.

Research design

The study is quantitative and the data was analysed through structural equation modelling (SEM) using the partial least squares (PLS) algorithm. The SmartPLS 3.0 software was utilized. While the covariance-based SEM (CB-SEM) is more popular. The viability of using PLS-SEM as a methodology has been gaining wide acceptance lately. This is due to its ability to handle large amounts of data and complex models. PLS-SEM can still demonstrate outstanding statistical power even when dealing with a small sample size (Hopkins, 2014)., hence it was selected for this study.

Data collection method

The electronic survey route was opted for due to COVID-19. Survey questionnaires are relatively cheaper and quicker than other methods like experiment, telephone surveys, literary texts, and focus groups. An electronic questionnaire developed using google forms was distributed in tech-industry Facebook groups based in Botswana, between October 2020 and January 2021. Through primary data the researcher was able to collect the data that is more consistent with the research question and hypothesis.

Participants

A total of 96 responses were collected and usable. The respondents consisted of the experts in risk management and collaborative innovation. The average year of experience for the respondents was approximately 5 years, rendering the population suitable to be a part of the study.

Research instrument

The 5-likert scale questionnaire included the measurement of five different types of five acquisition risks, four assimilation risks, five transformations risks, five exploitation risks, and four UIC Performance indicators. Thus 23 items altogether. These are portrayed in Table 1.

Table 1 Constructs and descriptions

Indicator	Sub-indicators
Acquisition risk	1. Minimal engagement in joint research projects beyond the industry (ACQR1) 2. Lack of periodical meeting with external experts within our industry for the (ACQR2) 3. Management DISCOURAGING the employees to use information sources within our industry (ACQR3)

	4. Minimal emphasis from management regarding procuring information from outside the company (ACQR4) 5. In our company it is NOT appreciated when employees procure information from other industries (ACQR5)
Assimilation risk	1. Inadequate communication of IUC ideas across all departments (ASSR1) 2. Minimal emphasis of cross-departmental support by management during IUCS (ASSR2) 3. Lack of periodical cross-departmental meetings to interchange new ideas, problems and IUC achievement (ASS3) 4. Clash amongst employees of our company and university when communicating with each other on a cross-departmental basis (ASSR4) 5. Lack of a shared lingo for intra-corporate communication between company and university (ASSR5)
Transformation risk	1. Inability to structure and use collected knowledge by employees (TRAR 1) 2. Failure of employees to apply new knowledge in their practical work (TRAR2) 3. Company policy discouraging employees to engage in further training and continuous learning (TRAR3) 4. Employees not used to absorbing new knowledge for further processing (TRAR4) 5. Lack of tools to enhance knowledge that secures the company's competitiveness (TRAR5)
Exploitation risk	1. Management not supporting the development of prototypes /(EXPR1) 2. Company not converting innovative ideas into patents (EXPR2) 3. Failure to re-assess strategies and incorporating necessary alterations (EXPR3) 4. Delays in launching products from collaborative projects

	- EXPR5 Inability to work effectively by adopting new technologies
IUC performance	1.Number of patents (IUCP1) 2.Number of joint seminars (IUCP2) 3.Number of joint publications (IUCP3) 4.Number of new product launches (IUCP4)

Data Analysis

Three major steps that were followed to analyse the model were. (a) Model specification; (b) outer model evaluation; and (c) inner model evaluation.

Model Specification

Constructs can either be exogenous or endogenous. Exogenous constructs are also known as independent variables, whereas endogenous constructs act as dependent variables (Hopkins, 2014). In this case, acquisition risk, assimilation risk, transformation risk and exploitation risk are exogenous/independent variables while industry-university collaboration performance is an endogenous/dependent variable. The initial model is depicted in figure 2 below.

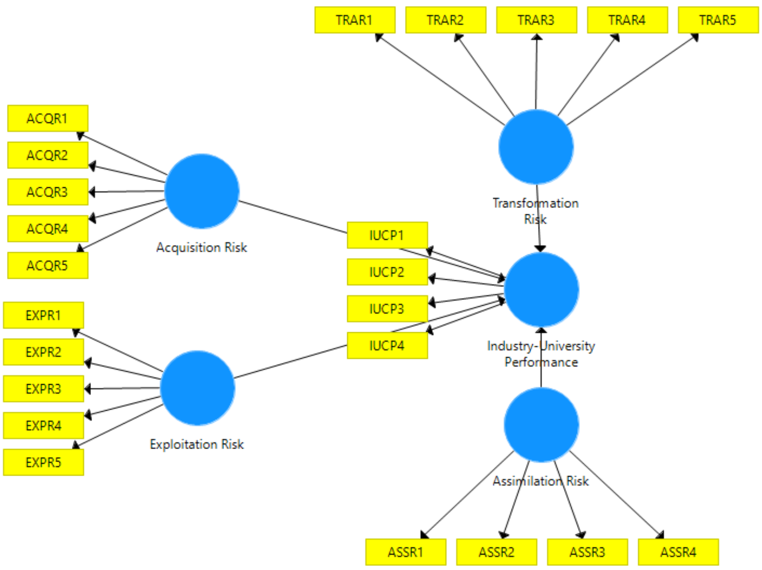

Figure 2 Model specification

Outer Model Evaluation

The outer model evaluation step involves running the PLS-SEM algorithm, and then the reliability and validity of the outer models is assessed. The **composite reliability** measures the internal consistency of the constructs. Through the use of composite reliability, PLS-SEM is able to cater for different indicator reliabilities. *Composite reliability coefficients* that range between 0.60 and 0.70 are deemed as appropriate in exploratory studies, whereas other types of research label the coefficients of 0.70 and 0.90 as satisfactory (Nascimento and Macedo, 2016)

The validity on the other hand is assessed through the following two techniques; **convergent validity** and **discriminant validity**. A convergent validity is only accepted for each item with an outer loading of over 0.70 and when the construct's average variance extracted (AVE) is 0.50 or greater. The AVE refers to the mean value of the squared loadings of a couple of indicators. The discriminant validity describes the extent to which the construct is empirically not similar to the rest of the constructs .(Nascimento and Macedo, 2016).

Inner Model Evaluation

Once the measurement model is satisfactory, the next step is to assess the structural model also known as the inner model. This is computed to do the hypothesis testing and the bootstrapping technique is utilized to yield the significance of each coefficient. Finally the predictive accuracy of the model is calculated using the blindfolding procedure and measured using Q^2. The value of Q^2 is supposed to be greater than 0 .(Nascimento and Macedo, 2016).

RESULTS

The findings of the study are split into two parts; the outer model results and the inner model results.

Outer Model Results

Firstly, the path diagram of the measurement model was processed to detect whether the yielded coefficients of both the outer and inner model were significant. The initial output is shown in Table 2 and Figure 3.

Table 2 Inner model CR and AVE before adjustment

	Composite Reliability	Average Variance Extracted
Acquisition risk	0.837	0.550
Assimilation risk	0.885	0.682
Exploitation risk	0.951	0.795
Industry-University performance	0.409	0.287
Transformation risk	0.939	0.763

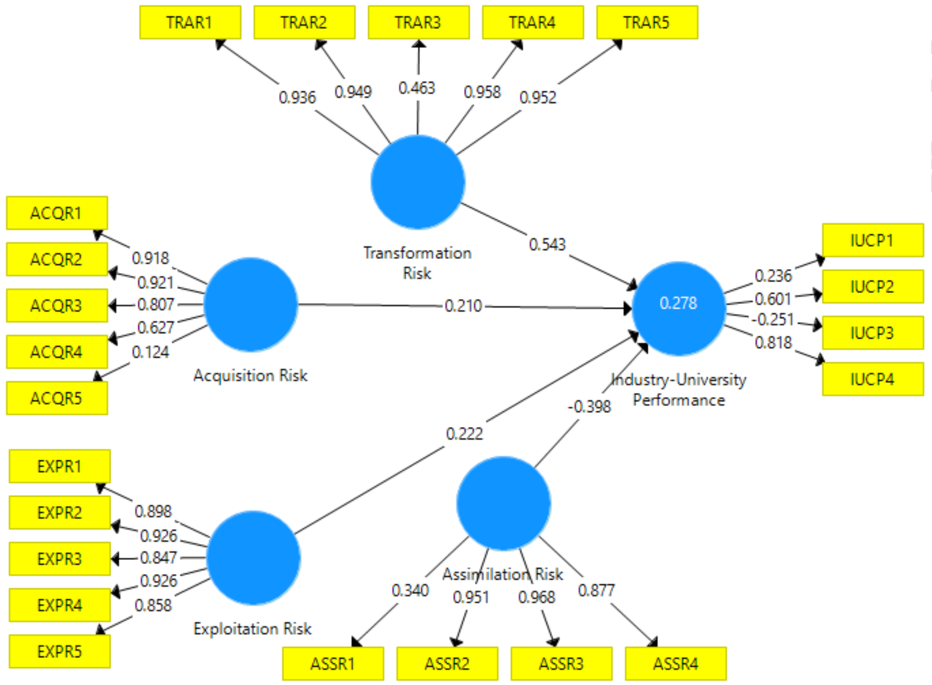

Figure 3 Initial outer loadings before adjustments

The constructs were refined by deleting some variables with Outer Loadings lower than 0.6 threshold (see figure 3), and the **Average Variance Extracted (AVE)** lower than 0.5, see Table

2 and **Composite reliability** lower than 0.7 see Table 1 (Nascimento and Macedo, 2016). In this light, the indicators IUP3, IUP1, ACQR 5, and TRAR3 were deleted.

After deletion the new **outer loadings** were assessed. Figure 4 indicates that all the loadings were now greater than 0.6 with the exception of IUP2 (0.561), which is approximately 0.6 and the rationale for retaining it.

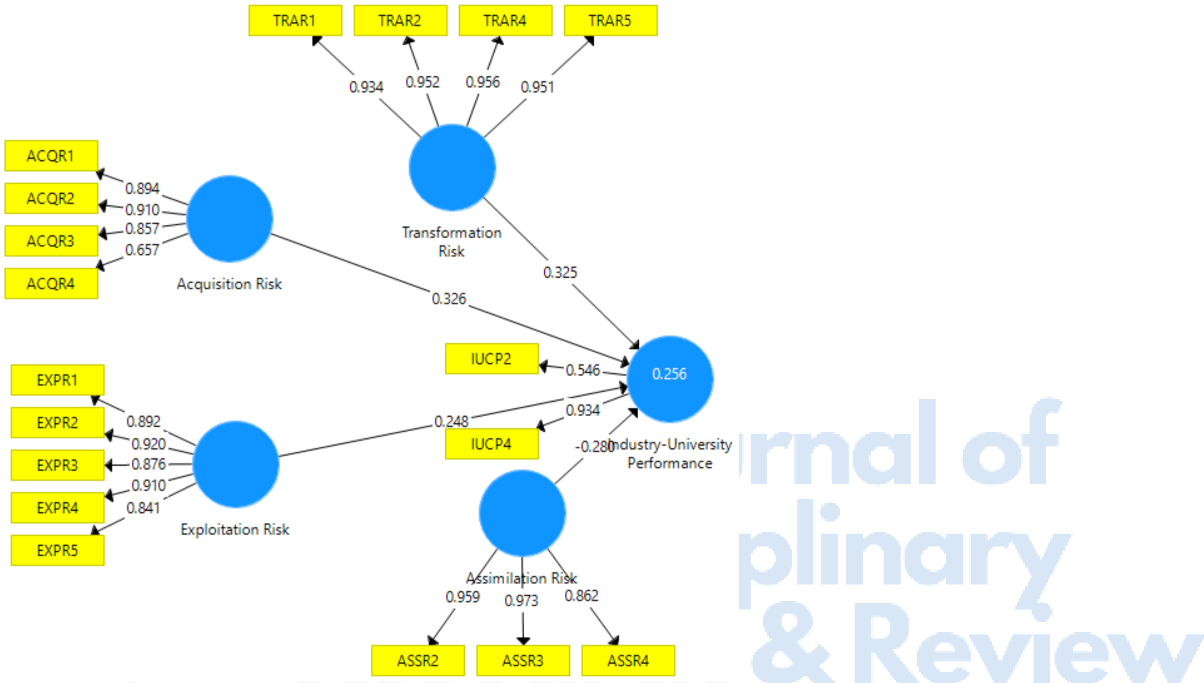

Figure 4 Loadings after adjustments

The ***discriminant validity*** of the Inner model were also measured using **Heterotrait-Monotrait Ratio (HTMT)** and transformation risk by exploitation risk had a number slightly higher than the threshold 0.9 (Nascimento and Macedo, 2016) as shown in figure 5.

	Acquisition Risk	Assimilation Risk	Exploitation Risk	Industry-University Performance	Transformation Risk
Acquisition Risk					
Assimilation Risk	0.167				
Exploitation Risk	0.244	0.834			
Industry-University Performance	0.655	0.245	0.483		
Transformation Risk	0.128	0.838	0.901	0.568	

Figure 5 HTMT matrix

The two constructs (transformation risk and exploitation risk) were tested for correlation using **Value inflation factors (VIF) values** and the variables with a VIF greater than 5 were deleted one by one until the HTMT was improved. As such the variables TRAR4 and TRAR5 were excluded from further processing of the model. The final **HTMT** for all the constructs was less than 0.9 as shown in figure 6 and the loading for IUP2 increased to 0.715 (see figure 7).

	Acquisition Risk	Assimilation Risk	Exploitation Risk	Industry-University Performance	Transformation Risk
Acquisition Risk					
Assimilation Risk	0.192				
Exploitation Risk	0.256	0.822			
Industry-University Performance	0.622	0.261	0.441		
Transformation Risk	0.173	0.842	0.881	0.568	

Figure 6 Final HTMT values

The author did further processing and deleted ACQR4 as it had loading of less than 0.7 and the loading of IUP2 further increased to 0.727 as shown in figure 7.

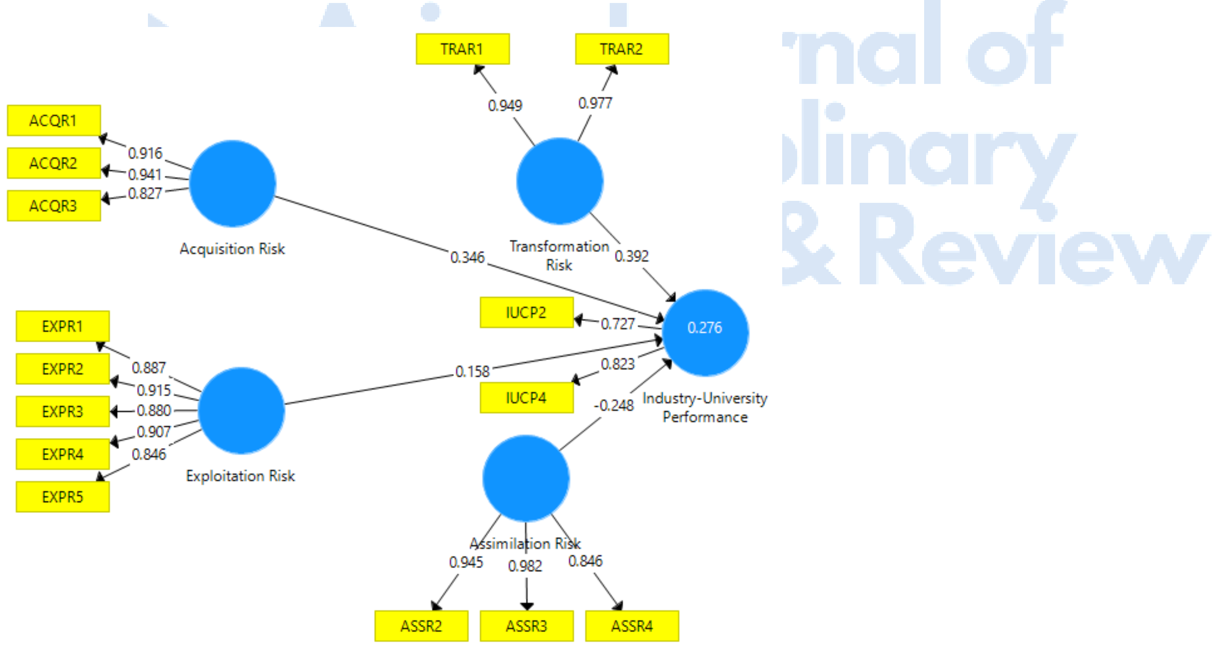

Figure 7 Final model after processing

Inner Model Results

To conduct ***hypothesis testing*** the significance of the path coefficients were estimated by analyzing the T-test values which were acquired by performing a non-parametric bootstrapping procedure. The critical value of T using a two-tailed test is 1.96 at the significance level 5%. The bootstrapping procedure findings are shown in Table 3.

Table 3 Hypothesis testing results

Hypothesis		t-Statistic	Result
H1	*Acquisition risk is negatively related to IUC performance*	**0.346**	**Supported**
H2	*Assimilation risk is negatively related to IUC performance.*	-0.248	Not Supported
H3	*Transformation risk is negatively related to IUC performance.*	**0.392**	**Supported**
H4	*Exploitation risk is negatively related to IUC performance.*	0.158	Not Supported

Table 3 above displays the bootstrap results for examining the correlation between the independent and dependent latent constructs. According to the results ***Hypothesis 1 and 3*** are supported with the t-statistics values 1.96 (0.346 and 0.392 respectively). On the other hand, ***Hypothesis 2 and 4*** are not supported as the t-statistics values are less than 1.96 at level of P<0.05. These outcomes confirm that acquisition risk and transformation risk contribute negatively to IUC performance.

Finally, the ***predictive relevance*** is reported. As shown in figure 8 the predictive relevance for the resultant model is greater than 0 (0.14) and therefore deemed as fit.

	SSO	SSE	Q^2 (=1-SSE/SSO)
Acquisition Risk	288.000	288.000	
Assimilation Risk	288.000	288.000	
Exploitation Risk	480.000	480.000	
Industry-University Performance	192.000	166.100	0.135
Transformation Risk	192.000	192.000	

Figure 8 Predictive relevance of the model

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DISCUSSION

This section offers a discussion of results presented in the previous section. The findings are based on one main research question; do Absorptive Capacity risks negatively influence Industry-University Performance in the context of Botswana high tech Industries? The question seeks to answer which of the following identified risk factors; Acquisition risk, assimilation risk, transformation risk and exploitation risk negatively affect IUC performance in the context of Botswana tech industry.

The results suggest that the relationships between exploitation risk and IUC performance, as well as assimilation risk and IUC Performance and are not statically significant. Therefore, the exploitation and assimilation are the strong point of high tech firms collaborating with universities in Botswana.

Only Acquisition Risks and IUC performance and transformation Risks and IUC performance are significant statically. This means that as the acquisition and transformation risks increase, IUC performance decreases and a decrease in these two risk categories will translate to an increase in the IUC performance.

When dealing with several sources of ACAP risks in the Botswana high tech Industry, "Minimal engagement in joint research projects beyond the industry", "Lack of periodical meeting with external experts within our industry", and "Management discouraging employees to use information sources within the industry" are the prominent acquisition risk factors negatively influencing IUC performance and consequently managers should pay attention to them in order to take necessary actions to mitigate them.

Additionally, transformation risks need special attention too when collaborating with universities (Lütjen *et al*., 2019), (Cheng and Chen, 2010), and (Aliasghar *et al*., 2019). Particularly structuring and using collected knowledge by employees (TRAR 1) and applying new knowledge in their practical work (TRAR2) should be a top priority to endure a successful collaboration.

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CONCLUSIONS

The paper‘s main aim was to better understand the relationship between ACAP risks and IUCs performance. Therefore a PLS-SEM approach was employed to assess whether several ACAP risks such as acquisition risk, negatively influence Industry-university collaboration in the context of Botswana high tech industries. After collecting data from 96 respondents in the Botswana tech industry, the paper concludes that the tested framework is statistically fit in terms of its convergent validity, internal consistency reliability, and discriminant validity.

The T-statistics reveals that the relationships between exploitation risk and IUC performance, as well as assimilation risk and IUC Performance and are not statically significant. Only Acquisition Risks and IUC performance and transformation risk and IUC performance are significant statically. Additionally, the value of Q^2 proves the relevance of the model.

The insights will help managers strategically position firms through developing policies for reducing ACAP risks. Thus, establishing fruitful collaborations between these two very different types of organization.

Finally, it worth noting that this study has some limitations. First, the data was only collected in Botswana. Secondly, it is only focused solely in the high tech industry. Thirdly, the analysis was made using only 96 observations. Future research should explore different industries and other method such as Artificial Neural Networks should be employed. Finally, a larger sample size should be considered for better representation.

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