Information Resources Management Journal

Volume 32 • Issue 4 • October-December 2019 • ISSN: 1040-1628 • eISSN: 1533-7979
An official publication of the Information Resources Management Association

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Volume 32 • Issue 4 • October-December-2019 • ISSN: 1040-1628 • eISSN: 1533-7979

An official publication of the Information Resources Management Association

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Information Resources Management Journal
Volume 32 • Issue 4 • October-December 2019

Selecting the Most Desirable IT Portfolio Under Various Risk Tolerance Levels

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ABSTRACT

To better assist decision-makers (e.g., enterprise executives) in selecting the most desirable IT portfolio, this study proposes a new IT Portfolio Efficient Frontier model that incorporates the decision-maker's risk tolerance levels. The proposed model, built on portfolio optimization along with experimental design and simulation data, considers three IT portfolio scenarios: even distribution-based IT portfolios, uneven distribution-based IT portfolios, and dominant IT portfolios. Our findings show that the IT portfolio efficient frontiers derived from both an even distribution-based IT portfolio and an uneven distribution-based IT portfolio have a relatively positive relationship between IT portfolio risk and return. Our findings also indicate that if IT investments are part of a dominant IT portfolio, an inflection point of the IT portfolio efficient frontier appears under the decision-maker's medium risk tolerance level, and the most desirable IT portfolio is generated when a decision maker's risk tolerance level is medium or higher.

KEYWORDS

Efficient Frontier, Enterprise Executives, IT Portfolio Management, Risk Tolerance Levels

INTRODUCTION

In 2018, global information technology (IT) spending grew by 6.2% to $3.7 trillion US dollars according to the latest forecast by the research firm Gartner, Inc. (2018 https://www.gartner.com/newsroom/id/3871063). Chan et al. (1997) found that the "fit" between information systems (IS) and business objectives is significantly associated with the performance of a firm. In fact, evidence increasingly shows that investment in IT can produce value at a variety of organizational levels. At the firm level, research has demonstrated that IT investment translates into profitability (e.g., Mithas et al., 2012). Meanwhile, a number of IS researchers have drawn attention to the concept of IT Portfolio Management (ITPM), a system for managing the total IT-related investments within an enterprise (Weill and Vitale, 2002), and ITPM is expected to improve the performance of IT investment (Jeffery and Leliveld, 2004). With regard to a firm's IT resources, IT portfolios can be thought of as a bridge that connects projects to the firm as a whole. The concept of ITPM is similar to the concept

DOI: 10.4018/IRMJ.2019100101

of financial portfolio management, but a significant difference is that IT investments are not liquid, as are stocks and bonds in the financial market. As a result, IT investments may need to incorporate both financial and nonfinancial methods for evaluation (Betz, 2007).

IT-driven business activities are enabled by IT investment projects; however, there is very limited research on IT (project) portfolio selection issues in the ITPM domain. Hence, the motivation of this research is to propose a new decision-making model to assist enterprise executives in selecting the most desirable IT portfolio when dealing with IT investments under various risk tolerance levels. Our study follows the argument of Aral and Weill (2007) that a firm should determine its IT investment allocation based on its strategic priorities. In line with Bhatt and Grover (2005), and Kohli and Grover (2008), making appropriate strategic IT investment choices is a critical capability for maximizing firm performance in the long run. On the other hand, Dewan et al. (2007) indicate that IT investments are much riskier than non-IT capital investments, as measured by their relative contributions to the overall riskiness of the firm. For these reasons, this study addresses the following research question: "How can a firm select the most desirable IT portfolio to improve the efficiency of IT resource allocation under different risk tolerance levels?"

The proposed new methodology, including the IT Portfolio Efficient Frontier model, is composed of concepts from Data Envelopment Analysis (DEA) and the Modern Portfolio Theory (MPT), as well as a risk assessment component, to articulate the risk tolerance levels of decision makers. Specifically, the proposed model, built on portfolio optimization along with experimental design and simulation data, will be able to consider three IT portfolio scenarios: (1) even distribution-based IT portfolios, (2) uneven distribution-based IT portfolios, and (3) dominant IT portfolios. Even distribution-based IT portfolios would include a low level of variance in the size and scope of the individual IT investment projects while uneven distribution-based IT portfolios would involve a high level of variance. Dominant IT portfolios would include a very large (dominant) IT investment project along with a number of smaller projects.

The study contributes to our understanding of ITPM research and practice. The proposed methodology, including the IT Portfolio Efficient Frontier model, can be considered to be a new approach in the ITPM literature, and practitioners may leverage the proposed new model to boost the performance of IT portfolios based on various risk tolerance levels of decision-makers (e.g., senior executives) when making IT investment decisions. The remaining sections are organized as follows. The next section reviews the related theoretical studies and this is followed by a description of the proposed IT Portfolio Efficient Frontier model. Use of the proposed model is then illustrated with a hypothetical example and computational analysis. The paper concludes by presenting the main findings and identifying directions for future work on this research topic.

THEORETICAL BACKGROUND

Ensuring projects are aligned with strategy to achieve portfolio balance is regarded as the foundation of project portfolio management (Clegg et al., 2018). Further, the Modern Portfolio Theory (MPT) refers to the principles underlying the analysis and evaluation of rational portfolio choices based on trade-offs between risk and return when considering investment decisions (Markowitz, 1959). In line with the portfolio theory, the portfolio choice that involves greater return and less risk is considered to be superior (e.g., more efficient) than the portfolio choices that involve less return and greater risk. Compared to conventional financial investments such as stocks and bonds, IT investments are considered non-liquid investments and IT portfolio management is the application of systematic management to large classes of items managed by enterprise IT groups (Bentley and Davis, 2009). To better cope with the relationship between risk and return while making decisions about IT portfolio selections, this study aims to develop a risk assessment method to evaluate IT investment risk based on established theory that is incorporated into the proposed IT Portfolio Efficient Frontier model.

Portfolio Theory

With reference to finance literature, a basic definition of portfolios is a collection of investments owned by an institution or an individual, and portfolio management involves analysis of different investments as a whole. Though widely applicable across different fields, many studies show that the Modern Portfolio Theory (MPT) has had a significant impact on the practice of portfolio management. In particular, MPT is able to provide a framework for constructing and selecting portfolios based on the expected performance of the investments and the risk appetite of the investor (Fabozzi et al., 2002). In this regard, the MPT could be seen as the only theory pertaining to IT portfolio management in prior IS research, since the portfolio value and risk balance is its centerpiece (Markowitz, 1952).

Furthermore, the MPT asserts that the balanced portfolio choice is the most efficient choice because it involves the highest portfolio value for a given portfolio risk. Although these dominant choices might present different values associated with risk, they are equally efficient choices. Along with the portfolio choice built on the MPT, two fundamental aspects need to be considered: diversification and the trade-off between expected return and risk (Brandt, 2009). In accordance with this perspective, risk aversion is closely related to portfolio diversification, and rational risk-averse investors should be able to make a portfolio selection from these efficient portfolio choices (Kijima and Ohnishi, 1993).

IT Portfolio Management (ITPM)

Following the implementation of the Sarbanes-Oxley Act, many enterprise investment decisions have been strictly scrutinized. Thus, investment issues have become a greater concern for many senior executives. As a consequence, an increasing number of firms are under pressure to implement more effective IT investment controls. For ITPM it follows that enterprise IT should be managed as the information capital of an enterprise. Since IT projects account for most IT spending, they need to be considered on the same enterprise level as portfolios. Therefore, the centerpiece of IT portfolio management is project selection and resource allocation (Chiang and Nunez, 2013). For this reason, IT project selection turns out to be an essential business problem, because most IT components are customized for an enterprise through project implementation (Cho and Shaw, 2013).

According to Jeffery and Leliveld (2004), the definition of ITPM is to manage IT as a portfolio of assets through a method similar to the management of a financial portfolio along with striving to improve the performance of the portfolio by balancing risk and return. A firm's IT portfolio is its total investment in computing and communication technology (Weill and Vitale, 2002), or the sum total of all of its IT projects. In this respect, IT portfolios are a bridge that connects the project level to the firm level in terms of internal strategic resource allocation (Zhu, 2003; Jeffery and Leliveld, 2004; Ray et al., 2005). To improve the performance of IT investments, ITPM aims to manage IT assets as a whole through a method similar to managing financial portfolios (McFarlan, 1982; Bardhan et al., 2004; Weill and Aral, 2006), along with nonfinancial methods for evaluation (Betz, 2007). Hence, the key motivation for decision-makers using ITPM is to select the most desirable IT portfolio to achieve a specific IT-driven strategic goal more efficiently and eventually improve firm performance.

IT Productivity, Data Envelopment Analysis (DEA) and IT Portfolio Management (ITPM)

Prior research shows that production theory has been widely applied for assessment of productivity, and this theory suggests that firms are able to transform various inputs (e.g., costs) into outputs (e.g., returns) using a production function to reveal the relationship between inputs and outputs (Nicholson and Snyder, 2011). Further, inputs are regarded as resources that are intended to be minimized, whereas outputs are regarded as outcomes that are intended to be maximized (Morita and Avkiran, 2009). In accordance with Hitt and Brynjolfsson (1996), the production theory can be used to evaluate IT investments in connection with IT productivity. Since organizations ideally allocate IT resources to achieve maximum productivity for a firm, IT productivity addresses the relationship between a firm's

IT-related investments and its associated efficiency gains such as financial returns. For example, both labor expenditure and capital investment are considered as critical firm resources, thus utilizing both of them within the IT function is able to enhance IT productivity that leads to the organization's growth (Berndt, 1991; Hitt and Brynjolfsson, 1996; Bharadwaj, 2000).

Among production functions, the Data Envelopment Analysis (DEA) model is known as a non-parametric approach and a linear fractional programming model and it has been widely used as an objective multi-criteria decision-making method (Lawrence and Kleinman, 2010). The key feature of the DEA model is to uncover hidden relationships between multiple inputs and outputs, and therefore it does not have any limitation when selecting the inputs and outputs (Zhu, 2003). Further, Ayabakan et al. (2017) explore the impact of IT on operational capabilities in the context of production processes and show that the DEA approach can estimate IT-enabled production capability. Referring to the financial economics literature, the relationship between return and risk is positively linear, whereas the relationship between return and risk in IT investments could be non-linear (Tanriverdi and Ruefli, 2004). ITPM is now widely seen as a management practice in the IT investment context, and the goal of ITPM is to manage the information capital at the individual and the enterprise level. Particularly, the objectives of ITPM implementation are to plan, measure and optimize the business value of enterprise IT. In line with Cho (2010), motivated by the potential non-linear relationship between return and risk in IT investments, the DEA model can be seen as an appropriate model to address the heterogeneous metrics of inputs and outputs in the ITPM context. For a comprehensive view of the DEA model in the ITPM context, this paper summarizes the model's (1) assumptions and (2) contributions below:

1. Assumptions:
   a. The proposed DEA model does not assume a linear output and input relationship for IT investments;
   b. This research assumes that the overall IT budget of the firm was already allocated to multiple business units/divisions in order to accomplish their strategic goals;
   c. All observed production possibilities are feasible;
   d. In this research, when the inputs and outputs of IT investments in a project are considered in the production process, the efficiency scores generated by the DEA model can be used to represent IT project value;
   e. With the assumption of constant returns to scale, any proportional change in input leads to the same proportional change in output;
2. Contributions:
   a. The DEA model is an analytical tool for determining effective and ineffective performance as the starting point for inducing theories about best-practice behavior (Charnes et al., 1995);
   b. The DEA model examines the decisions among alternatives that have high uncertainty (Linton et al., 2002);
   c. The DEA model has been widely used as an objective multi-criteria decision-making method (Lawrence and Kleinman, 2010);
   d. The DEA model is known as a non-parametric approach and a linear fractional programming model that is capable of coping with non-linear relationships between the inputs and outputs. Therefore, it can be used with heterogeneous metrics of inputs and outputs in the ITPM context (Cho, 2010);
   e. Sowlati et al. (2005) present a model within the DEA framework for prioritizing IT projects.

There is no need for the DEA model to include explicit mathematical forms between inputs (e.g., costs) and outputs (e.g., returns), thus this feature of the model will uncover hidden relationships among multiple inputs and outputs. To address the unique characteristics of the DEA model, this study mainly focuses on the two most common types of DEA model: the DEA - CCR model and the

DEA - BCC model. The DEA - CCR model would be applicable when assuming constant returns to scale (Charnes et al., 1978). However, if this assumption does not hold, the DEA - BCC model proposed by Banker et al. (1984) should be used instead. Consequently, the DEA - BCC model is primarily used to accommodate variable returns to scale.

Efficient Frontier and IT Portfolio Management (ITPM)

To reduce portfolio risk through diversification, the MPT has been widely used in practice by embracing financial instruments that are not perfectly correlated over the past few decades. With reference to Markowitz (1952, 1959), a simple criterion of investment selection can be a ratio between return and risk, thus an efficient portfolio provides the highest portfolio return for given portfolio risk or the lowest portfolio risk for given portfolio return. Rational decision-makers take into account each balanced portfolio choice and tend to select the highest portfolio return for given portfolio risk. For instance, if one portfolio's return is higher than the return of another, and both have the same risk, the portfolio with the higher return is more efficient than another one. More importantly, a series of balanced portfolio choices, which are known as dominant choices, form the efficient frontier. The efficient frontier is also recognized as a graphical illustration that represents the optimal combination of risk and return.

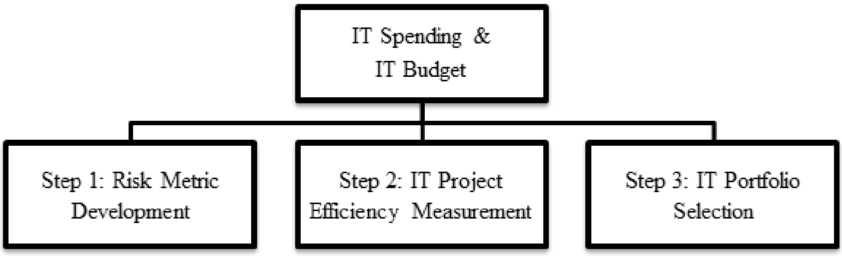
Prior studies proposed several computational approaches for portfolio prioritization (e.g., Bardhan et al., 2004; Chiang and Nunez, 2013; Cho and Shaw, 2013). The ITPM problem can be thought of as an optimization problem concerning IT resource allocation issues, and enterprise executives may need to identify measurable strategic objectives embraced by various business units. When dealing with ITPM problems, the decision-makers (e.g., senior executives) intend to incorporate all of the possible IT portfolio attributes to address a fundamental question, which is how to maximize return or minimize risk. In response to this need, this study aims to assist a firm in building an IT portfolio with relevant attributes that performs well in the context of the firm's IT resource allocations to better achieve enterprise business objectives.

Along with the experimental design and simulation data, the central goal of this research is to provide various alternative business scenarios to illustrate IT resource allocations as references for enterprise executives so they can select the most appropriate IT portfolio to achieve their enterprise strategic goals efficiently. In terms of ITPM, both the DEA and the MPT are applicable to measure the performance of IT (project) portfolios by taking into account relevant attributes (e.g., cost, risk and return). Specifically, prior to the project implementation, incorporating risks into the project portfolio management processes gives the enterprise executive a better understanding of the evaluation of project management success as well as the allocation of resources (Teller et al., 2014). This study utilizes the concept of an efficient frontier to demonstrate the optimal combination of selected IT portfolio attributes (e.g., cost, risk and return). Accordingly, the results will include a series of balanced IT portfolio choices (also known as efficient choices) that form the IT portfolio efficient frontier as the final outcome.

MODEL DEVELOPMENT

Along with risk metric development, attaining efficient frontiers from the DEA and MPT is a new methodology for firms to identify their most desirable IT portfolio among all of their portfolio choices. Regarding each proposed initiative, IT portfolio decisions are made by a steering committee comprised of the IT executive and business executives who account for IT governance within the firm (Karhade et al., 2015). As a result, a steering committee can benefit from the proposed model, referred to as the IT Portfolio Efficient Frontier model, to make optimal IT investment decisions. This process is outlined in Figure 1 and this section provides more details to justify each step of the proposed model.

Figure 1. IT portfolio efficient frontier model



Step 1: Risk Metric Development

Financial literature defines risk as the standard deviation of return and considers a portfolio to be a weighted combination of assets (Markowitz, 1959). Decision theory defines risk as each action that leads to one of many possible specific outcomes with known probabilities, which are assumed to be known by the decision maker (Hansson, 1994). Since IT investments are more likely to be considered non-liquid investments, Dewan et al. (2007, 2011) indicate that IT investments are much riskier than non-IT capital investments. From the IS standpoint, risk can be quantified by assessing the probability of occurrence and a financial consequence for each alternative (Pearlson and Saunders, 2010), thus risk is perceived as the possibility of additional cost or loss due to the choice of alternatives. In particular, the IT project is the main tactical level activity through which IT projects translate to business results for the enterprise (Huang et al., 2013), and IT projects are often distinguished from many non-IT projects on the basis of their high levels of risk (Lientz and Larssen, 2006). As such, understanding investments in IT projects and the associated IT portfolio is of great importance for enterprise executives, since their risk tolerance level (risk appetite) in the context of IT investment decision making is in line with the firm's IT strategy (Karhade et al., 2015).

Risk is an essential piece when assessing IT project efficiency. According to A Guide to the Project Management Body of Knowledge (PMBOK® Guide) from the Project Management Institute (2013), project risk is "an uncertain event or condition that, if it occurs, has a positive or negative effect on one or more project objectives such as scope, schedule, cost, and quality. A risk may have one or more causes and, if it occurs, it may have one or more impacts" (p. 310). With regard to IT projects, risk is the possibility of an unfavorable outcome of the final project deliverable (Kumar et al., 2008). In addition, utility theory (Keeney and Raiffa, 1993) is used to represent the preference of a decision-maker for various levels of a performance measure, and if appropriate utility is assigned to each possible consequence, the expected utility of each alternative is calculated. The most efficient action is the alternative with the highest expected utility. With reference to Clemen and Reilly (2013), three common risk attitudes based on utility curves of various decision-makers are: (1) Risk-Averse: Concavity in a utility curve implies that an individual has a risk-averse attitude, called a concave (opening downward) utility curve, (2) Risk-Seeking: Convexity in a utility curve implies that an individual has a risk-seeking attitude, called a convex (opening upward) utility curve, and (3) Risk-Neutral: Risk neutrality is reflected by a utility curve that is simply a straight line.

The preference for various levels of each performance measure may be different, so Step 1 of the proposed model presents a risk assessment method that embraces concepts from the Technical Performance Measure (TPM) and utility function to measure risk (Browning et al., 2002). More specifically, risk measurement is the integral of the products of probability P(x) and the loss of each unachieved outcome, which is calculated by $\left[U\left(X_T\right)-U\left(X\right)\right]$. To evaluate the probability of an identified risk and its effects on objectives (Wang et al., 2010), the possible value of a performance measure is represented by a Probability Density Function (PDF). Following these premises, this study presents three different return levels: the most likely return, the worst-case return, and the best-case return, by using the triangular probability distribution shown in Figure 2.

In this study, risk can be viewed as the product of an event's likelihood and the exposure or loss if the event occurs, thus the definition of risk value (risk score) is the probability that the return falls under the managerial expectation (X_T) of decision-maker for each IT project associated with its utility function, as shown below:

$$R_i = \sum_i wi * \left\{ k * \int_{-\infty}^{X_T} P(x)\left[U(x_T) - U(x)\right] dx \right\}$$

The proposed risk assessment method components, including its relevant variables and definitions, are shown in Table 1.

Step 2: IT Project Efficiency Measurement

Tanriverdi and Ruefli (2004) and Dewan and Ren (2011) discuss the importance of incorporating risk into the IT business performance analysis and emphasize the impact of IT investments on the risk-return relations of firms. Based on the concept built from the Data Envelopment Analysis (DEA) model while measuring the efficiency of the Decision-Making Unit (DMU), the DEA model's unique feature is to transform the ratio of multiple inputs and outputs into a linear fractional program with a scalar measurement ranging between 0 (the worst) and 1 (the best) (Tone, 2001). While taking into account the nature and complexity of the relation, the DEA model is regarded as a proper multi-attribute model for estimating IT-related risks and costs as inputs and returns as outputs. Additionally, Sowlati et al. (2005) present a model within the DEA framework for prioritizing Information Systems (IS) projects. Since an IT project is the main level that translates IT activity into business results, IT (project) portfolios can be thought of as a pool of heterogeneous IT projects within a firm. Consequently, Step 2 will prioritize the IT projects by considering each IT project as a DMU, and the quantitative model for IT project efficiency measurement is shown below:

$$\text{Max } E_j = \frac{uy_j - u_0}{v_1 x_{1j} + v_2 x_{2j}}$$

Figure 2. Triangular probability distribution

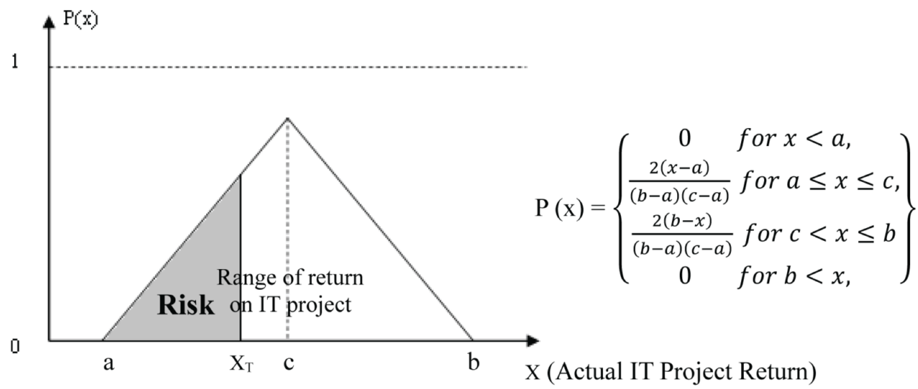


Table 1. Risk assessment method variables and definitions

Variable	Definition
a	Worst-case return for an IT project
b	Best-case return for an IT project
c	Most-likely return for an IT project
x	Actual return on an IT project
x_T	Managerial expectation for an IT project
P(x)	Likelihood of achieving the return on an IT project
U (x_T)	The utility value of managerial expectation for an IT project
U(x)	The utility value of actual return on an IT project
k	A normalization constant
w_i	The percentage of budget spending over total budgeted cost on an IT project
R_i	Risk (value)

$$\text{Subject to} \frac{uy_j - u_0}{v_1 x_{1j} + v_2 x_{2j}} \leq 1$$

j = 1… n

$$u, v_1, v_2 \geq \varepsilon$$

The variables and definitions for the proposed model are shown in Table 2. The variable u_0 is a free variable that is defined by DEA, particularly in the variable returns to scale (VRS) model (e.g., DEA - BCC model). However, if u_0 is zero, the model above will be considered an application of the constant return to scale (CRS) model (e.g., DEA - CCR model).

Step 3: IT Portfolio Selection

Selecting the most appropriate projects for a project portfolio can be thought of as a decision problem (Meier et al., 2017), and the management of risks is a major component of project portfolio management (Teller and Kock, 2013). To select the most applicable IT portfolio choice, the aim of Step 3 is to develop a quantitative model to address the IT portfolio selection as shown below. In most cases, when decision criteria are outlined in Modern Portfolio Theory (MPT), the selection rationale is grounded in the portfolio balancing various decision attributes, including cost (C), risk (R), and return (V). Each portfolio is constructed by selecting a set of candidate IT investment projects, and the selected IT portfolio choices will be able to provide the highest return corresponding to the risk tolerance level of a decision-maker. According to Dia (2009), the generation of a portfolio performed by a mathematical model optimizes the weighted sum of the Decision Making Units' (DMU) efficiency ratios, which can produce an optimal value of selected choices that reflect the preferences

Table 2. IT project efficiency measurement model variables and definitions

Variable	Definition
x_{1j}	Estimated cost of IT project j
x_{2j}	Estimated risk of IT project j
y_j	Estimated return of IT project j
E_j	The efficiency of IT project j
u	The weight on the return
u_0	Free-in-sign variable
v_1	The weight on the cost
v_2	The weight on the risk

of a decision-maker. The equations for Step 3 are shown below. The variables and definitions for the proposed model can be found in Table 3. And π is defined as a vector representing a set of selected IT projects, also known as an IT project portfolio:

$$Max\, I\left(\pi\right) = \sum_{j=1}^{n} E_j S_j$$

$$\text{Subject to}$$

$$uy_j - v_1 x_{1j} - v_2 x_{2j} \leq 0$$

$$\sum_{j=1}^{n} uy_j \geq E_j$$

$$\sum_{j=1}^{n} S_j x_{ij} \leq X_i$$

$$\sum_{j=1}^{n} S_j y_{ij} \geq Y_i$$

$$\sum_{j=1}^{n} S_j \leq n$$

$$S_j = 0 \text{ or} 1$$

i = 1… t
j = 1… n

$$u, v_1, v_2 \geq \varepsilon$$

Table 3. IT portfolio selection model variables and definitions

Variable	Definition
I	Optimal score of a selected IT portfolio
S_j	The selected IT project(s) in the portfolio
X_i	The maximal amount of inputs to be considered in the IT portfolio
Y_i	The minimal amount of outputs to be considered in the IT portfolio
E_j	The efficiency of IT project j
x_{1j}	Estimated cost of IT project j
x_{2j}	Estimated risk of IT project j
y_j	Estimated return of IT project j
u	The weight on the return
v 1	The weight on the cost
$v2$	The weight on the risk

HYPOTHETICAL EXAMPLE AND COMPUTATIONAL ANALYSIS

Hypothetical Example and Experimental Design

This study responds to the challenge of firm IT project portfolio selection. An illustration of this challenge follows:

αβ is a Fortune-500 enterprise where IT investment governance has been listed among the top management issues. To prepare a short list of the "most desirable" IT project portfolio choices, αβ's steering committee, comprising the IT executive and business executives, is going to have an evidence-based meeting to determine the best investment allocation strategy among all of the desirable IT project portfolio choices.

This illustration could happen at almost any enterprise. There is a set of i desirable IT projects from x1, x2, to xi for the portfolio selection. Based on the hypothetical data in Table 4, there are three main IT project types: (1) Customer Experience Improvement – an IT project that is expected to generate a certain portion of marginal financial return and improve customer satisfaction after implementation, (2) Infrastructure Cost Optimization – an IT project that may have negative financial return but significant impact on business processes, and (3) Improved Process Efficiency – an IT project that is expected to generate high financial return with longer completion processes. Beyond these options, any combination of IT projects could be the portfolio choice. The two most extreme instances are portfolios composed of none of the IT projects ({}) or composed of all of the IT projects ({x1, x2, …, xi}). For example, if 30 IT projects are to be selected, there could be more than 1,000,000,000

Table 4. Hypothetical IT project data

ID	IT Project Name	Project Type	Return on Investment (ROI)
#1	J2EE platform migration	Customer Experience Improvement	4.7%
#2	Mobile payment plan	Customer Experience Improvement	4.5%
#3	Contract management system upgrade	Customer Experience Improvement	2.7%
#4	Operating system upgrades	Infrastructure Cost Optimization	-3.8%
#5	Underwriting system upgrade	Customer Experience Improvement	2.2%
#6	Life and auto policy web interface	Improved Process Efficiency	10.0%
#7	Installations of a new database system	Infrastructure Cost Optimization	-5.4%
#8	Client e-notice system	Customer Experience Improvement	8.0%
#9	Partnership e-credit plan	Customer Experience Improvement	9.9%
#10	Deployment of new computers and memory upgrades of servers	Infrastructure Cost Optimization	-7.9%
#11	Debt/lending data analysis plan (BI)	Improved Process Efficiency	11.1%

portfolio choices (2^30). Finally, by incorporating cost, risk and return in the proposed model, the n IT portfolio choices can be selected as the “candidates” for the IT portfolio.

Specifically, this study only uses a small data set in this hypothetical example in order to facilitate the understanding of the model’s use. The numbers used in this example are disguised because of the investment information protection agreement with the Fortune 500 company.

Three IT project portfolio scenarios are considered when using the proposed IT Portfolio Efficient Frontier model to address IT resource allocation. The characteristics of these three scenarios, as well as descriptive statistics for the simulated IT portfolio data, are shown in Table 5. The hypothetical example assumptions include: (1) the three scenarios (i.e., even distribution-based IT portfolio, uneven distribution-based IT portfolio, and dominant IT portfolio) each have the same budget for IT investment projects, and (2) each specific IT investment project will apply the same utility function across the three scenarios.

Results From Computational Analysis

To determine the optimal decision in regard to the risk tolerance level of a decision-maker, the three scenarios are considered when using the proposed IT Portfolio Efficient Frontier model to address the desirable IT portfolio choices from an extremely high risk tolerance level (i.e., aggressive risk tolerance level) to a very low risk tolerance level (i.e., conservative risk tolerance level). Specifically, based on the experimental setting of this study, the risk tolerance levels are set from 0.2 to 0.8. Therefore, the derived aggressive portfolio choice’s risk will be no more than 80% of the original overall IT project risk, while the derived conservative portfolio choice’s risk will be no less than 20% of the

Table 5. Simulated IT portfolio data characteristics and descriptive statistics

Scenario 1	Variable	Average	Std. Dev.
Even Distribution-based IT Portfolio (All IT project sizes are included between one Std. Dev of the Mean value)	Cost ($ Million)	$ 2	$ 0.05
	Return ($ Million)	$ 2.06	$ 0.13
Scenario 2	Variable	Average	Std. Dev.
Uneven Distribution-based IT Portfolio (Around half of the IT project sizes are out of the range of one Std. Dev of the Mean value)	Cost ($ Million)	$ 2	$ 0.58
	Return ($ Million)	$ 1.95	$ 0.74
Scenario 3	Variable	Average	Std. Dev.
Dominant IT Portfolio (Along with multiple small project sizes in an IT portfolio, there is at least one IT project size that is larger than two Std. Dev. of the Mean value)	Cost ($ Million)	$ 2	$ 2.94
	Return ($ Million)	$ 2.11	$ 3.19

original overall IT project risk. This setting follows heuristics, and the exact settings in the enterprise are very contingent. More detailed computational results are shown in Table 6, Table 7, and Table 8.

Referring to the results in Table 6, the IT portfolio efficient frontier generated from the even distribution-based IT portfolio scenario appears as a slight upward curve, which shows that the IT portfolio risk has a significant positive relationship with the IT portfolio return. Along with the extremely high risk tolerance level of a decision-maker, the firm will be able to gain its optimal

Table 6. Even distribution-based IT portfolio scenario under different risk tolerance levels

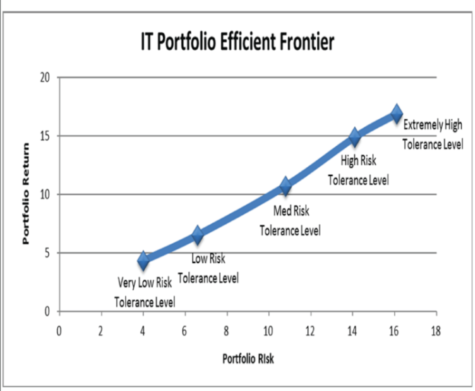
The IT efficient frontier is derived by maximum return in a given risk limit	Risk Tolerance Levels	The selected # IT project(s) in the desirable IT portfolio
	Extremely High 0.8	{1, 2, 3, 5, 6, 7, 8, 9}
	High 0.65	{1, 2, 3, 5, 6, 9, 11}
	Med 0.5	{1, 2, 6, 9, 11}
	Low 0.35	{1, 6, 9}
	Very Low 0.2	{1, 9}

Table 7. Uneven distribution-based IT portfolio scenario under different risk tolerance levels

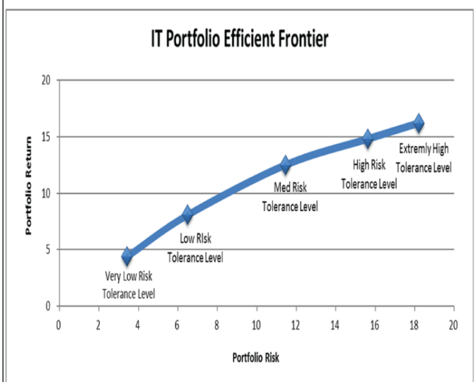
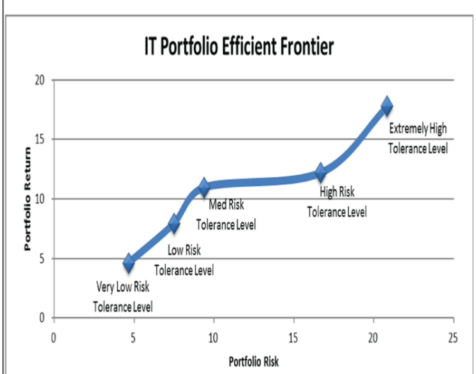
The IT efficient frontier is derived by maximum return in a given risk limit	Risk Tolerance Levels	The selected # IT project(s) in the desirable IT portfolio
	Extremely High 0.8	{1, 2, 3, 4, 5, 6, 9, 10, 11}
	High 0.65	{1, 2, 3, 5, 6, 9, 11}
	Med 0.5	{1, 2, 3, 5, 9, 11}
	Low 0.35	{1, 2, 3, 5, 9}
	Very Low 0.2	{1, 2, 5}

Table 8. Dominant IT portfolio scenario under different risk tolerance levels

The IT efficient frontier is derived by maximum return in a given risk limit	Risk Tolerance Levels	The selected # IT project(s) in the desirable IT portfolio
	Extremely High 0.8	{1, 4, 5, 7, 8, 10}
	High 0.65	{8}
	Med 0.5	{1, 2, 3, 4, 5, 6, 7, 9, 10, 11}
	Low 0.35	{1, 4, 5, 6, 7, 9, 11}
	Very Low 0.2	{1, 5, 9, 11}

portfolio value by mainly selecting the Customer Experience Improvement-oriented IT projects mixed with a small number of Improved Process Efficiency-oriented and Infrastructure Cost Optimization-related IT projects in the even distribution-based IT portfolio.

Based on the results in Table 7, the IT portfolio efficient frontier from our proposed model resembles a slight concave curve because there is a diminishing marginal return to risk. Additionally, the slight concave relationship between risk and return indicates that if a firm's IT investment projects are represented by an uneven distribution-based IT portfolio scenario, this firm may be able to achieve its optimal IT portfolio value with the medium risk tolerance level of a decision-maker. Also, referring to the common risk attitudes, this type of IT portfolio (opening downward curve) may perform well if the decision maker has a risk-averse attitude. Along with the medium risk tolerance level of a decision-maker, the firm will be able to gain its optimal portfolio value while mainly selecting the Customer Experience Improvement-oriented IT projects mixed with an extremely small number of Improved Process Efficiency-oriented IT projects in the uneven distribution-based IT portfolio.

In this study, the dominant IT portfolio is considered to be an important case of the uneven distribution-based IT portfolio to demonstrate how a firm pursues a specific IT-driven strategic goal that is implemented by at least one large IT project along with multiple smaller projects in an IT portfolio. Hence, the results in Table 8 show that if IT investment projects resemble the dominant IT portfolio scenario, an inflection point of the IT portfolio efficient frontier appears under the medium risk tolerance level of the decision-maker. Before the inflection point, the results show a downward curve, which is similar to a concave curve. The enterprise executives may consider a conservative investment strategy before reaching the inflection point, and the firm will be able to gain its optimal portfolio value by selecting all of the IT projects except an extremely large sized IT project. On the other hand, after the inflection point, the results of this study indicate an upward curve, which is similar to a convex curve. The enterprise executives may consider an aggressive investment strategy after reaching the inflection point, and the firm will be able to gain its optimal portfolio value by selecting an extremely large sized IT project mixed with a number of Infrastructure Cost Optimization-related projects and Customer Experience Improvement-oriented IT projects.

CONCLUSION AND FUTURE RESEARCH

Based on the experimental design and simulation data, this paper considers three scenarios for tackling IT investment decisions: even distribution-based IT portfolios, uneven distribution-based IT portfolios, and dominant IT portfolios. Moreover, this study assumes that these three scenarios utilize the same IT budget and IT spending for their IT project portfolios. More importantly, this study assumes that senior executives will have consistent risk tolerance levels to deal with all of the IT investment projects; meanwhile, each specific IT investment project across the three types of IT portfolio scenarios is assigned the same utility function in the hypothetical example of this paper. Accordingly, the results of this paper show that if IT investments are similar to the even distribution-based IT portfolio, then IT portfolio efficient frontiers may resemble a slight upward curve. On the other hand, if IT investments are comparable to the uneven distribution-based IT Portfolio, the IT portfolio efficient frontiers may appear as a slight concave relationship between risk and return. If IT investments are like the dominant IT portfolio, the IT portfolio efficient frontiers may resemble a concave curve before reaching its inflection point. However, the IT portfolio efficient frontiers may appear to be a convex curve after reaching its inflection point.

For managerial interpretation, the IT portfolio efficient frontiers of both the even distribution-based IT portfolio and the uneven distribution-based IT portfolio indicate that IT portfolio risk has a relatively positive relationship with IT portfolio return. In this regard, the results may match the fundamental concept of financial investment; that is, low risk investment yields low return, while high risk investment yields high return. Furthermore, regarding all of the portfolio choices in the dominant IT portfolio, the results of this study show that the most desirable IT portfolio choice could be generated with the senior executive's medium or higher risk tolerance level. Hence, if a firm intends to accomplish a specific IT-driven strategic goal that is implemented by at least one large IT project along with multiple smaller projects in an IT portfolio (similar to the dominant IT portfolio), it would be a good approach for senior executives to consider an aggressive investment strategy after reaching the inflection point of the IT efficient frontier. In particular, a senior executive who has a higher risk tolerance level with the same IT budget and IT spending across the three types of IT portfolio scenarios (i.e., even, uneven and dominant) may get the most desirable IT portfolio choice when reaching the turning point.

In terms of future work in this domain, a large-scale simulation including interactions with the three steps to complement the initial illustrative example could be used to extend the findings from this study. Empirical IT portfolio data could also be used to test the proposed model and consider additional forms of IT investment project scenarios. The findings from this simulation-based study provide the basis for reassessment of the proposed IT Portfolio Efficient Frontier model using firm-level empirical data in a range of industries.

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Information Resources Management Journal
Volume 32 • Issue 4 • October-December 2019

The Influence of the Entrepreneur's Open Innovation Strategy on Firm Performance:
Empirical Evidence From SMEs in Kenya

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ABSTRACT

This article helps identify the main factors influencing the performance of small and medium agribusiness enterprises in Kenya. The study proposes five research hypotheses, each tested on a sample of 150 agribusiness enterprises using multiple regression analysis. The results show that the use of external partners, such as scientific research establishments and commercial consultants, influences the firm's performance. This influence is moderated by factors like internal capabilities and the firm's degree of openness to innovation.

KEYWORDS

Entrepreneurship, Firm Performance, Internal Capabilities, Open Innovation, SMEs, Sources of Knowledge

1. INTRODUCTION

Open innovation (OI) represents a more encompassing framework for understanding the phenomenon of generating value via innovation (Zhang et al., 2018; Schroll and Mild, 2011). The concept developed by Chesbrough (2003) has established important strategies in the world of business, institutional and academia. It represents a new way of looking at innovation as a new paradigm shift for functional innovation process and research. Thus, the concept has enlisted major concern for researchers, managers, and policymakers in analyzing innovation as an interactive process rather than an exclusive one (Chesbrough, 2003). Small and medium enterprises (SMEs) are more inclined to succeed in their innovation activities by using a wide range of spectrum of partners and external knowledge to take advantage of their expertise, to overcome the limits of their resources and to share uncertainties and costs related to innovation activities (Fakhreddine, Amara, and Landry, 2012).

It is in this perspective that this paper pursues to understand better the concept of the OI process in SMEs. The particular choice of SMEs can be explained in particular by their presence in the industrial fabric of the majority of countries and their importance in job creation. Moreover, SMEs are often considered as a bastion of innovation (Becheikh, Landry, and Amara, 2006; Massa and Testa, 2008).

Innovation activities are also one of the most important factors of international competitiveness, productivity, production and employment performance of many countries (Lee, Park, and Park, 2010). In recent years, innovation has become one of the main concerns of business leaders who want to

DOI: 10.4018/IRMJ.2019100102

penetrate new markets, increase their profitability and improve the value of their goods and services (Barrett and Wynarczyk, 2009; Barron, Hultén, and Hudson, 2012). The review of the literature reveals the complex nature of OI, given the existence of various internal and external factors whose interactions influence a firm's innovation activities and performance (Huizingh, 2011).

The concept of OI has been widely studied in the context of large companies (Chesbrough, 2003; Criscuolo, Haskel, and Slaughter, 2010; Laursen and Salter, 2006, 2004; Lichtenthaler, 2008). Some researchers have analyzed the over-all effect of OI on organizational performance and recognized the positive effect of such aspects as involvement of firms with OI (Chaston and Scott, 2012), OI inclination (Hung and Chiang, 2010), the publication of OI events (Noh, 2015), OI capabilities (Ahn, Minshall, and Mortara, 2013), OI application (Huizingh, 2011), open search strategies (Cruz-Gonzalez, Lopez-Saez, and Navas-Lopez, 2015), technology association portfolio (Faems et al., 2010). Most of these studies have focused on the effect of incoming external knowledge and found a direct positive effect of external knowledge sourcing on firm performance (Vrontis et al., 2016; Wang, Chang, and Shen, 2015). However, these studies did not focus on the entrepreneur's OI strategy when analyzing the OI aspects and the studies were not sector specific. Furthermore, researchers have used the concept of absorptive capacity to understand the contingency of OI on firm performance (Wang, 2018). SMEs require appropriate knowledge basis and compatible cognitive ability to integrate and transform external knowledge. Such capabilities are highly reliant on the firm's strategic behavior and human resource. Thus, some researchers proposed that entrepreneur open innovation strategy is important but ignored component of firm technology absorption capacity and performance (Jelonek, 2015; Huggins and Thompson, 2017). Studies that have focused on open innovation within agribusiness enterprises remains rare.

Agribusiness sector in Kenya contributes about 25% of the GDP. Despite this, the sector still performs below its potential due to climate change, inadequate technical skills and inadequate collaborations with research institutions. Furthermore, the sector contributes 18% of the total formal employment with about five million smallholder farmers engaged in agribusiness enterprises (AGRA, 2017; Oduor et al., 2018; GOK, 2016). The government has identified agribusiness sector as a major component in attaining economic development through the transformation of subsistence farming to an innovative commercial sector that would guarantee food security by the year 2020 (Ong'ayo, 2017).

However, agribusiness enterprises operate in an increasingly turbulent environment characterized by financial crises, globalization of trade and the new knowledge economy. According to Broughton (2011), during the economic crisis, SMEs were most affected compared to large firms (Wymenga et al., 2012). This reflects the fact that most of SMEs have fewer resources in terms of human, financial, and technological resources in relation to large companies to withstand the pressure of environmental instability (Barron, Hultén, and Hudson, 2012). In order to be successful, SMEs has no choice but to increase the effectiveness of its innovative strategies and adapt them to the context of uncertainty (OECD, 2005). According to previous researchers (Barrett and Wynarczyk, 2009; Barron, Hultén, and Hudson, 2012), innovation is considered a fundamental element of economic gains and social factors contributing to the achievement of competitive edge in both regional and international markets (Oltra, Flor, and Alfaro, 2018).

Entrepreneur's innovation strategy represents an array of relationships, ability, and communication with external stakeholders. Thus, firm challenges may arise due to the complexity of these relationships and how the firm manage them to gain competitive advantage. Entrepreneur strategic mechanisms play a critical role in enhancing or lessening OI efficiency. Thus, the main objective of this article is to assess how firm ought to align their human resources strategies with their open innovation practices to ensure profitability of small agribusiness enterprises, which is little explored, especially in developing countries. The paper attempts to answer the following questions; Do SMEs adopting an opening strategy obtain better results in innovation? Do internal human resource competencies moderates the relationships between the OI and firm performance?

The remainder of this paper is organized as follows. The second section discusses the literature review with the detailed theoretical context that describes different theories related to the concept of OI and SMEs. The third section deals with the research methodology adopted by putting the focus on the sample profile, the instrument of measurement, sequence and research design employed. Section 4 presents the results while section 5 covers discussion of the results. The final section covers study implications and recommendations for future research.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The term OI refers to 'shared innovation between stakeholders' (Chesbrough, 2003). It defines the process by which a company is able to call on ideas and expertise outside its own walls, which enables them to profit from its ideas or patents outside its own market by offering them to other companies/institutions through R&D (Chesbrough and Bogers, 2014). The concept comprises several activities including an incoming process where the firm uses external partners to develop an innovation internally while harnessing their knowledge. Or outgoing (Inside-Out process) where the company collaborates with external partners in order to sell the ideas of its in-house developed innovation (Van de Vrande et al., 2009). OI conglomerates internal and external ideas into designs and methods whose necessities are defined by a commercial model (Chesbrough, 2006).

OI principles, therefore, describe how to deal best with strategic assets in order to meet market demands and company requirements (Gassmann, 2006; Gassmann, Enkel, and Chesbrough, 2010). OI involves the ability of a firm to use external sources of innovation to actualize their innovations without working on the complete solution alone (West and Gallagher, 2006). Thus, OI is founded on collective organizational associations, alliances, and corporations aimed at accelerating innovation for all shareholders (Dahlander and Gann, 2010).

Innovation is multidimensional and is defined essentially in four forms (products, processes, marketing and organizational) and in two intensities (incremental and radical) (Schumpeter, 1942). Innovation is not only a means of survival in the economy it is also an important driver of growth, productivity, and competitiveness that makes it possible to withstand the effects of ecological instability (Pittaway et al., 2004). SMEs are progressively deliberated as the critical source of new product development and new technologies (Hilmersson, 2014). In the current wake of a dynamic business environment, the continuing challenge for business stakeholders and policymakers is to identify and to support the factors that motivate SMEs in economic growth. Naturally, the encouragement of innovation in innovative SMEs is at the heart of these policy initiatives as these companies have significant economic growth potential (Wynarczyk, 2013).

Several researchers define SMEs differently because of the diversity of its characteristics. (Zeng, Xie, and Tarn, 2010). These definitions reflect the economic, cultural and social habits of each country and are often based on size or turnover. The accepted principles for the definition of SMEs comprise staff numbers, investment level, and sales volume. The European Commission defines SMEs as firms with 10 to 49 employees and medium-sized businesses as those with between 50 to 250 employees (Katua, 2014). In Kenya, the SMEs Act 2012 categories SMEs in terms of their sector, employee number, and investment value (Berisha and Pula, 2015).

2.1. The Concept of Open Innovation

According to Chesbrough (2003) the term 'open innovation' describe the innovation processes that companies use to interact with their environment, in order to discover and utilize outward resources (Van de Vrande et al., 2009; Chesbrough, 2003). Initial open innovation research focused on open innovation practices at the level of high-tech companies (Dodgson, Gann, and Salter, 2006; Piller and Walcher, 2006; Chesbrough, 2003). According to Dahlander and Gann (2010), several theoretical concepts underlying innovation go back to the 1990s (Cohen and Levinthal, 1990; Rosenberg, 1990; March, 1991).

OI reflects a less contradiction, unlike the closed innovation that has a continuum with varying degrees (Dahlander and Gann, 2010). Traditionally, large companies manage the innovation and development of new products like an internal process. They rely heavily on their own knowledge, R&D capabilities and technologies to create new products in their labs which represent strategic assets. This method, marked by Chesbrough (2003) as the concept of closed innovation (traditional), which has a considerable barrier to potential competitive advantage for SMEs in emerging nations. That is why this paper proposed the method of open innovation as a newly built strategy for management and for the commercialization of innovations, considering innovation as an imperative strategy to advance a market competitive advantage. Figure 1 shows the characteristics of closed and open innovation applicable to the contemporary business environment.

According to the literature review, open innovation is a broad construct that involves a variety of processes related to business innovation. Several researchers have approached the concept of open innovation in terms of incoming, outgoing and joint processes (Bianchi et al., 2010; Chesbrough, 2006; Gassmann, Enkel, and Chesbrough, 2010; Schwartz and Huff, 2010). According to Gassmann, Enkel, and Chesbrough (2010), open innovation comprises several activities including an incoming process where the firm uses external partners (suppliers and customers) to develop an innovation internally while harnessing their knowledge. Or outgoing open innovation (Inside-Out process) where the company collaborates with external partners in order to sell the ideas of its in-house developed innovation (e.g. licensing agreement). The firm can also use joint open innovation (Coupled process) where it collaborates with external partners with complementary skills to exchange knowledge and develop an innovation together (Zhang et al., 2018).

Managers are increasingly aware of the importance of capacity absorption to effectively manage the method of OI (Chesbrough and Di Minin, 2014). The use of external resources requires managerial capacities, science, and technology. These serve to assimilate knowledge and the know-how resulting from collaboration in OI. These abilities act as a regulator between external knowledge and innovation performance (Muscio, 2007; Tsai, 2009; Wang and Han, 2011; Ebersberger et al., 2012; Lasagni, 2012; Chen, Lin, and Chang, 2009). They represent a condition necessary to open innovation practices (inbound and outbound) of SMEs (Spithoven, Clatysse, and Knockaert, 2011), and must be sufficiently developed to absorb not only external knowledge (Laursen and Salter, 2006), but also to transfer the knowledge of the company to the partners (Lichtenthaler, 2008) as shown in Figure 2.

Figure 1. Elements of open and closed innovation

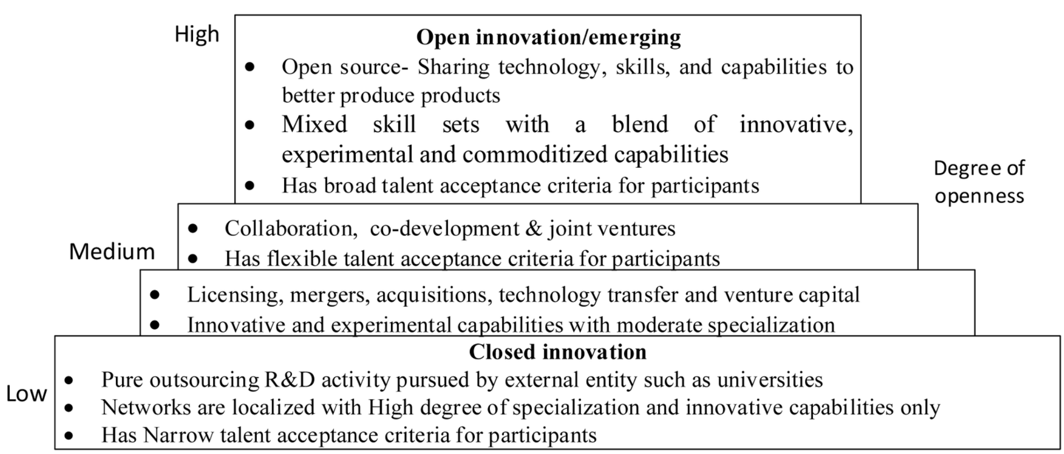
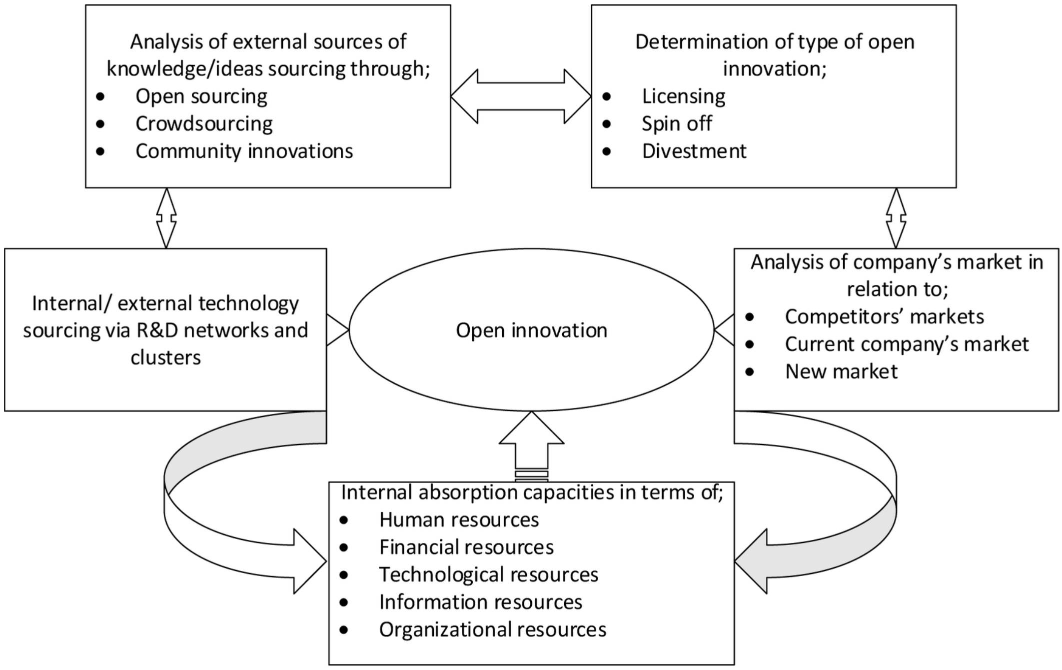


Figure 2. Study theoretical model



2.2. Open Innovation and SMEs Performance

Lee, Park, and Park (2010) point out that because of their resources, SMEs have a strong incentive to seek collaborations to generate economies of scale, reduce risks and increase the operational and commercial flexibility of their innovation activities. As such, Lichtenthaler (2008) list several motivations that drive SMEs to open up to the outside world: insufficient resources in R & D, the uncertain and increasingly competitive environment to more and more sophisticated customers and shorter product/service life-cycle in different sectors. Therefore, open innovation is proving to be a key strategy for the SMEs allowing it to find externally what lack internally. This represents support to consolidate knowledge already existing through new knowledge from resources and activities shared with its external partners (Chesbrough and Di Minin, 2014). This literature guided the study to formulate the following hypothesis:

H_1: There is a significant positive relationship between the degree of openness and innovation performance.

SMEs are increasingly vulnerable and exposed to constraints in terms of innovation capabilities, technical skills, management, and financing. Indeed, some of them do not have sufficient internal resources to diversify their product lines and invest in R& D (Bianchi et al., 2010; Van de Vrande et al., 2009). Chesbrough and Di Minin (2014) argues that some SMEs manage to develop significant inventions at a cost thanks to their specificities which represent a competitive advantage. Furthermore, Spithoven, Vanhaverbeke, and Roijakkers (2013) mention limits that prevent some agribusiness enterprises to innovate: the risk of adopting new ideas of more powerful companies, the weak financial capacity to pursue imitators and the ineffectiveness of patent protection (Mohnen and Raller, 2005). In an attempt to overcome these risks and constraints, SMEs use open innovation. This solution allows them to pool the resources and key innovation activities with external partners (Bianchi et al., 2010).

The implementation of an innovation project requires the availability of several resources within the company (Becheikh, Landry, and Amara, 2006). In this regard, the following section presents the different resources needed for the effective innovation process.

2.3. Human Resources

Staff must have managerial skills and technical abilities for organizing and sharing ideas from other employees and external partners, with the aim of supporting innovation (Lund Vinding, 2006; Becheikh, Landry, and Amara, 2006; Raymond and St-Pierre, 2010). According to these authors, the know-how and experience of highly qualified personnel to effectively perform the different tasks of the SME and also to be on the lookout for the different opportunities that the business environment can offer to carry out innovation projects is critical. The presence of highly qualified human resources, therefore, represents a determining factor for the success of the innovation strategy in SMEs. This strategy depends on the execution of the management policy of human resources (HR) which must be focused on innovation performance (Oke, Walumbwa, and Myers, 2012). As the lack of financial resources is a constraint for SMEs, it is often difficult to recruit qualified employees that are technologically and commercially innovative, which can be an obstacle for the successful implementation of innovation activities. Therefore, it is proposed that:

H_2: Human resource capacity will have a positive effect on the firm degree of openness and performance.

2.4. Financial Resources

Financial resources allow the realization of activities of SME innovation from the stage of the generation of the new ideas up to the marketing of the final product (Becheikh, Landry, and Amara, 2006; Raymond and St-Pierre, 2010; Canepa and Stoneman, 2008). They promote the recruitment of highly skilled employees and they promote the ability to access the latest inventions and technologies. In this sense, a lack of financial resources may represent an obstacle for managers and may prevent the completion of their innovation activities. The literature that addresses the issue of financial resources in SMEs reports a frequent lack of availability and accessibility to financial resources to innovate (Muthoni and Kithinji, 2013). This observation is linked to the particular financial characteristics of SMEs that do not allow them to easily access external sources of financing. This limit in financial capabilities represents a gap for these companies. This is an obstacle that can prevent them to start new projects independently and to carry out riskier innovations (Becheikh, Landry, and Amara, 2006). The inadequacy of equity and the difficulty of pledging the intangible assets of the SMEs make innovation activities more expensive (Mohnen and Raller, 2005; Gomes, Yaron, and Zhang, 2006). This is due to the premium risk that may be required by certain investors (Doh and Kim, 2014). SMEs managers should provide sufficient financial resources to cope with the dynamic business environment for effective process innovation. (Becheikh, Landry, and Amara, 2006). Therefore, it is proposed that:

H_3: Availability of financial resources will have a positive effect on the firm degree of openness and performance.

2.5. Technological Resources

According to (Oduor et al., 2018), technological resources refer to technical means such as tools, machines, instruments, processes, patents and the methods used to carry out production activities within the company. It turned out that the quality of the technological resources used in the innovation activities of SMEs is one of the most important factors that raise the level of innovation (Mohr, Sengupta, and Slater, 2010). Advanced technologies used in the innovation process has a positive effect on the SMEs' degree of innovation (Becheikh, Landry, and Amara, 2006). These have demonstrated that the use of advanced technologies promotes the success of innovation because it allows a better production efficiency that reduce time and cost of doing business. Therefore, it is proposed that:

H_4: Use of technological resources will have a positive effect on the firm degree of openness and performance.

2.6. Information Resources

Information resources consist of technological information that is strategic and commercially competitive (Bruque and Moyano, 2007). information resources enable the SMEs to cope with turbulence business environment and decipher the market requirements and competitor's strategic choices (Hewitt-Dundas, 2006). These resources are essential in that they help to reduce uncertainty about the results and the costs of innovation (Mohnen and Raller, 2005). In addition, they grant the opportunity to access innovative ideas from external partners, which facilitates carrying out innovation activities (OECD, 2005). In summary, the literature suggests that specific resources are essential to the realization of innovation activities. Thus, the study made a proposition as follows:

H_5: Access to information resources will have a positive effect on the firm degree of openness and performance.

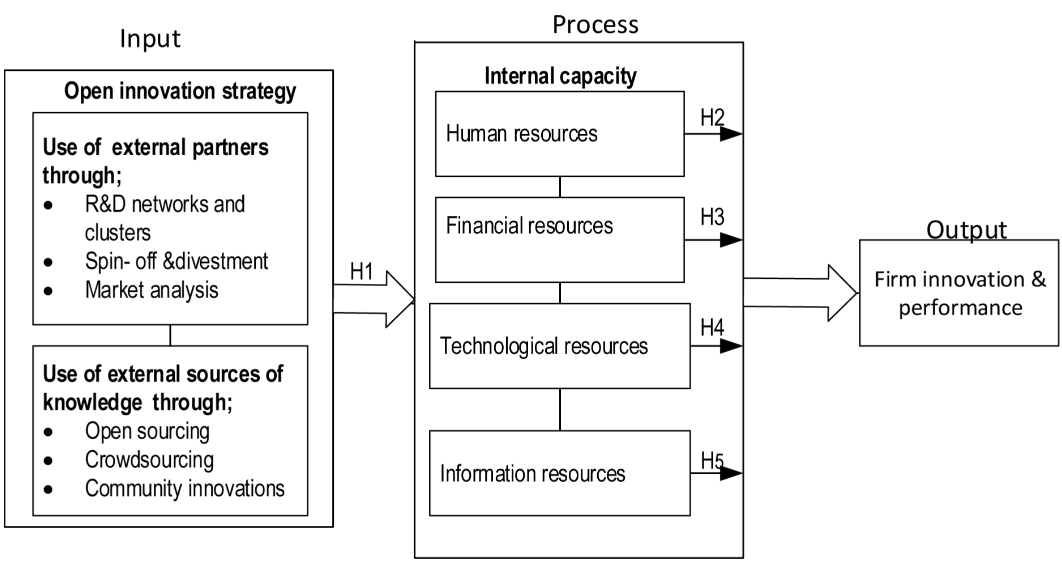
3. CONCEPTUAL FRAMEWORK

Figure 3 illustrates the conceptual framework of this research that shows the link between external partners, sources of external knowledge and firm internal capabilities.

3.1. Methods

The study used a quantitative research approach. The primary units of analysis of the study were the managers of agribusiness enterprises in Tharaka-Nithi County, Kenya. The

Figure 3. Conceptual framework



researcher selected this area because of the following; first, the county major economic activity is agriculture that comprises crop farming, beekeeping, fish farming, and livestock production. County's 98.2% percent of households engage in crop farming (ROK, 2017). The county 80% of land mass is arable. The county has underutilized arable land due to the low implementation of contemporary agronomic practices. Secondly, the county lies in a semi-arid area with great potential due to plenty of rivers emanating from Mt. Kenya that can provide water for irrigation.

To test the research hypotheses, the study used random sampling to select agribusiness enterprises registered and licensed by the County Government and funded by the Youth Enterprise Development Fund (YEDF). Previous studies have recommended various sample sizes and theories for determining an appropriate sample size (Guo, Pohl, and Gerokostopoulos, 2013; Binu, Mayya, and Dhar, 2014). However, sample-size requirements may vary according to the statistical analysis, and a variety of opinions observed in the literature, even when the same tools are applied. The sample that ranges between 10% to 30% is recommended when the components in the study sample are found to more than 30 elements (Mugenda and Mugenda, 1999). Based on the list of youth enterprise provided by YEDF there were 240 agribusiness enterprises from which a sample of 150 enterprises was obtained using a formula proposed by Israel (Israel, 2012) as follows:

$$n = \frac{N}{1 + N\left(e\right)^2} \tag{1}$$

where n =sample size, N = population size (240), and e = error term (0.05).

3.2. Sample Profile

The database used has 150 SMEs but the sample for our study was reduced to 109 enterprises given the missing information on some critical variables as shown in Table 1.

Table 1. Sample profile of SMEs by sector

Sector	Frequency	Percentage
Food and drink	25	23
Livestock	16	15
Textile and Clothing	12	11
Wood and Furniture	10	9
Metal products	5	4.5
Machinery/mechanic	6	5.5
Horney extraction equipment	4	3.5
Fish farming	5	4.5
Electrical and electronic products	8	7
Mineral water products	3	3
Distribution, wholesale trade	6	6
Miscellaneous services	9	8
Total	109	100

3.3. Questionnaire Design and Data Collection

Based on literature from open innovation, a questionnaire was developed to identify the relationship between the degree of openness and the performance innovation and assess the moderating effect of internal capabilities on the link between OI and firm performance. In order to assess the level of open innovation among SMEs, the questionnaire was designed in reference from relevant earlier papers as displayed in Table 1. The sample of 150 for this study met the requirement to use multiple regression analysis. The questionnaire items were validated in a pilot survey of 30 agribusiness enterprises. The questionnaire items were evaluated using a 5-point Likert-type-scale, where 1 = strongly disagree and 5 = strongly agree. Descriptive statistical analyses were also employed in order to analyze the profile information provided by respondents as shown in Table 2.

To improve response rate for the study, the researcher used an integrated method of questionnaire distribution where two trained research assistant used respondent's email, face-to-face and a mobile short message informing the respondents to check their emails and to indicate their convenience. The research assistant explained the purposes of the study, assured the anonymity of respondents and

Table 2. Variable constructs and indicators

No	Variable constructs and indicators (Measure)	Code
	Independent Variables- degree of openness	IV
	A. **Open innovation strategy**	OI
	i. Use of external partners	
1	Customers-consulting with its main current customers to learn about the evolution of their needs	CM
2	Market analysis -collaborates with customers to design and develop products, services, processes or equipment	CM1
3	Spin- off &divestment- collaborates with its customers to improve its products, services, processes or equipment	S&D
4	Use of R&D networks and clusters	R&D
5	Business association, Partnership and collaborations trade agreements	BAPC
6	Research institutes for business needs	RIBN
7	Consultants for techno scientific needs	RIBN1
8	Consultants for business needs	RIBN2
	ii. Use of external sources of knowledge	EK
1	Organization supporting innovation-The company participates in activities organized by support organizations	ORGS1
2	Crowdsourcing Information from technical support on products and processes, markets and the marketing,	CRD
3	Open sourcing-The company uses the services of economic development organizations in the region to innovate	ORGSI
4	Specialized research organization -The company collaborates with specialized research organizations to improve its products/services, processes or equipment	SRO
5	Community innovations by collaborations with research organizations to design and develop new products/services or processes	SRO2
6	Type of external knowledge- Information from technical support on products and processes	TK1
7	Information about markets and the marketing	TK2
8	Information that support R&D and new practice	TK3
	B. **Internal Capabilities**	IC
	i. Human Resources (HR)	HR
1	Employees have the opportunity to exchange with each other on matters relating to products, services or processes innovation	HR1
2	The company employs someone who has business skills in identifying new markets	BC1
3	The company employs someone who has the business skills to define strategies to market a new product or service	BC2
4	The company knows the maturity of its products	BC3
5	Learning capabilities - the company encourages members of its staff to increase their knowledge and skills through training	LC1
6	The company encourages staff to engage in innovative activities	LC2
7	The company encourages management to increase their skills and their knowledge of innovation management	LC3
	ii. Financial Resources (FR)	FR
1	The inadequacy of equity and the difficulty of pledging the intangible assets of the SMEs make innovation activities more expensive	FR1
2	Lack of financial resources deter our company innovative drive	FR2
3	The company have no adequate access to external sources of finance	FR3
	iii. Technology Resources (TR)	TR
1	The company attaches importance to the modernization of its processes in production	TR1
2	The company encourages and facilitates the adoption of new technologies	TR2
3	The company updates its equipment or technologies to avoid technological backwardness	TR3
	iv. Information Resources	IR
1	Information resource is essential in accessing firm innovative ideas from external sources	IR 1
2	Information resources enables the firm to cope with turbulent and competitive business environment	IR 2
3	Technological infrastructure facilitates access of information and innovation activities	IR 3
	Dependent variable - performance innovation in terms of % of sales attributable to:	DV
1	New products	PIN1
2	Products modified from R & D activities	PIN2
3	Products modified according to customer requirements	PIN3
4	Modified products as a result of a new technology	PIN4
5	Equipment/machinery improvement	PIN5
6	Production process improvement	PIN6
7	Original products and service	PIN7

their organization, explained how to fill and return the questionnaire. The researcher distributed 150 questionnaires, collected 115 out of which 109 were usable as shown in Table 2.

3.4. Respondents' Profile

The data in Table 3 show that 66% of the respondents were female, which reveals that female entrepreneurs have higher chances of doing business in the countryside. According to Gakobo (2013), most women in rural areas form more cohesive groups. The age bracket with the most respondents was the 31– 35-year-old bracket (40%), while the above-36 bracket accounted for 15%. The results show that most of the sample was youthful, which is significant to national development (ILO, 2015).

Most of the respondents (46%) had secondary education, while 4% had gained a master's degree and above; 10% had a degree, 25% had a diploma, and 15% had primary education. More than half of the respondents had only attained secondary education, a low rate. Previous studies also show that most small business owners have attained only secondary education (UNESCO, 2016). The respondents' level of education was important for the study because it influenced how the respondents interpreted the questionnaire. Most SMEs (40%) had between one and five employees; enterprises with six to 10 employees came next (35%). Most of the enterprises were in the manufacturing and agriculture sector (65%). Rural SMEs contribute to the informal employment that is significant to Kenya's economic growth (ILO, 2015).

4. RESULTS

To test the study hypotheses, Statistical Package for the Social Sciences (SPSS) version 21.0 was used, which was appropriate for quantitative data analysis (Carver and Nash, 2011; Meyers, Gamst, and Guarino, 2013). Preliminary tests, however, provide guidance on bivariate relations between the

Table 3. Sample characteristics

Item	Classification	Frequency	%
Gender	Male	38	34
	Female	71	66
Age	18-25 years	22	20
	26-30 years	27	25
	31-35 years	44	40
	Above 35 years	16	15
Business experience	Less than 1 year	5	5
	1-2 years	11	10
	3-4 years	44	40
	5-6 years	49	45
Education level	Masters	5	4
	Bachelors	11	10
	Diploma	27	25
	Secondary certificate	50	46
	Primary certificate	16	15
Industry category/sector	Crop production	63	58
	Livestock/dairy farming	21	19
	Fishing	15	14
	Beekeeping	10	9
Firm size	1-5 employees	44	40
	6-10 employees	38	35
	11-15 employees	16	15
	over 15 employees	11	10

different variables retained and constructed for the model. The first step, correlation analysis was performed to analyze the profile of the constructs of the study and to check if they present significant correlations. The results confirm that many study constructs had meaningful correlations, such that it's not possible to integrate each of the variables individually in the econometric model.

Secondly, since several of the variables of the study were correlated between them, the study used factor analysis in principal components to reduce the number of variables and ensure the independence of the relationships between the independent variables and also make the information less redundant. Principal Component Factor Analysis (PCA) is an exploratory technique whose object is to search, from a set of k variables measured on an interval, scales, or logic to show a structure underlying the data collected.

In a third step, multiple linear regression is performed to highlight the factors that play significant roles in performance innovation and the percentage of sales made by the firm. The linear regression is justified in the analysis statistics since it takes into account, only those factors that have a significant contribution to the explanation of the phenomenon studied. Thus, statistical checks of the significance of the introduced factors were performed at each stage of the analysis. In the fourth step, a moderate regression analysis was carried out in a more exploratory section to test the moderating effect of internal capabilities on open innovation. Information measuring the intensity of use of external partners were grouped into three factors.

4.1. Correlations Between Study Variables

The analysis between dependent and independent variables was done before conducting the multivariate analysis to assess the relationships between variables. Table 4 shows the correlations between the seven openness factors and the detailed percentages of sales attributable to the changes in partnership with customers for the last two years. The results show a positive correlation with sales from customer requests, which was expected, and sales from R & D activities. The findings indicate a significant correlation ($\beta = 0.298$, $p < 0.01$) between access to consultant information (RIBN1) and performance in sales.

Results in Table 5 indicate that there is a strong positive correlation ($\beta = 0.379$, $p < 0.01$) between business capacities (BC) and the partnership with customers (CM). Statistics also reveal a strong positive correlation ($\beta = 0.275$, $p < 0.01$) between HR and CM. Regarding partnership with specialized research organizations (SRO), the results show that there is a strong positive correlation ($\beta = 0.457$, $p < 0.01$) between technological resources and partnership with specialized research organizations (college, university or Government) (SRO). The results show a strong positive correlation between learning capabilities (LC) and access to consultant information (RIBN1) ($\beta = 0.358$, $p<0.05$).

Table 4. Correlations between the study variables

	Degree of openness						
	External partners		External sources of knowledge				
Performance innovation	CM	SRO	ORGSI	BAPCOB	RIBN	RIBN1	RIBN2
PIN1	-.024	.313	.060	-.050	.313	.298***	-.065
PIN2	.322**	-.081	-.250*	.013	-.085	-.019	.321**
PIN3	.328**	.027	.092	.047	.145	.044	.064
PIN4	.072	.147*	.182	-.216	-.039	-.052	-.028
PIN5	.152	.179**	.171	.055	.038	.063	.313**
PIN6	.191	.195*	.125	-.067	.025	.014	.074
PIN7	-.171	-.168*	-.082	.081**	-.129	-.063	.482**

*** P < 0.001; ** p < 0.05; * P < 0.10.

Table 5. Correlations between the factors of the degree of openness and the factors of internal capabilities

		Internal capabilities			
Degree of openness		**Capacities**		**Resources**	
		BC	LC	TR	HR
External sources of knowledge	CM	.379***	.272**	.181	.457***
	SRO	-.050	.130**	.626**	.062
	ORGSI	-.081	-.104	.517*	-.227
External partners	BAPCOB	.179*	.281**	.261	-.315
	RIBN	.260	-.036	.173	-.081
	RIBN1	.319	.372**	.273**	.097
	RIBN2	-.045	.312	.519	.358**

*** P < 0.001; ** P < 0.05; * P < 0.10.

Regarding the relationship between internal capabilities and innovation performance, the results in Table 6 show the correlations between the four internal capacity factors and the detailed percentages of sales attributable to changes in technological resources for the last two years. The result shows a strong negative correlation ($\beta = - 0.364$, $p < 0.01$) between these resources and the percentage of sales attributable to unmodified products (PIN7). Concerning human resources, the results reveal a strong positive correlation ($\beta = 0.387$, $p < 0.01$).

4.2. Test of Hypothesis

Table 7 present the results obtained from two multiple linear regression analysis. In model 1, the results highlight four significant relationships at a confidence level of 10%, with the performance innovation attributed to external partnerships and the two others attributed to access to external knowledge. Access to support information on marketing, information on new innovation practices and business consultants (RIBN2) explained positive significant results ($\beta = 0.187$, $p < 0.05$) with performance innovation which support the first hypothesis (H_1). Similarly, access to support information (ORGSI) ($\beta = 0.052$, $p < 0.001$) marketing and supporting information on new practices with research institutions had positive results, likewise collaboration with specialized research organizations (SRO) ($\beta = 0.085$, $p < 0.005$) to improve design and develop products or services indicated positive results on the firm performance. In model 2, the results show that the addition of internal capacity factors to the degree of openness in the second model brings out a significant relationship between human resources (HR) ($\beta = 0.032$, $p < 0.001$) and firm's degree of openness which supports H_2. Regarding financial resources, the results show a negative regression coefficient which is nonsignificant ($\beta = -.152$, $p >$

Table 6. Correlations between the 4 internal capacity factors and percentages of sales growth

	Internal capabilities			
Performance innovation	**Capacities**		**Resources**	
	BC	LC	TR	HR
PIN1	.084	.291	.083	.091
PIN2	.382	.081	.279**	.387***
PIN3	-.073	-.109	.064	.041
PIN4	.045	-.013	.064	.322
PIN5	.061	-.158	.265	.255
PIN6	-.047	-.031	.264*	.053
PIN7	-.064	.322	-.364***	-.238*

P < 0.01***; P < 0.05**; P < 0.10*.

Table 7. Result of multiple linear regressions of Degree Impact openness on innovation performance

	Model 1		Model 2	
	Regression Coefficient	Signification	Regression Coefficient	Signification
Degree of openness				
External partners				
CM	.063	.209	.052	.254
SRO	.085**	.005	.085	.120
ORGSI	.052***	.001	.185	.224
External knowledge				
BAPCOB	-.029	.427	-.034	.023
RIBN	.156	.162	.125	.160
RIBN1	-.225	.665	-.041	.638
RIBN2	.187	.213	.117	.082
Internal Capacities				
HR			.032***	.000
FR			-.152	.207
TR			.025**	.003
IR			.053***	.001
Adjusted R^2	.089	.123		
F-statistics	3.590	.234	3.218	.074

P < 0.01***; P < 0.05**; P < 0.10*.

0.001), thus H_3 is not supported. The results reveal the importance of financial resources in SME's opening innovation activities. Regarding the influence of technological and information resources on firm performance innovation, the findings show significant results TR ($\beta = 0.025$, $p < 0.05$) and IR ($\beta=0.053$, $p < 0.001$) which supports H_4 and H_5 respectively (see Table 8). In addition, the adjusted coefficient of determination ranges from 0.089 to 0.142.

4.3. Variables Interactive Effects

Regarding the moderating effect of internal abilities on the relationship between degree openness and performance innovation, the results in Table 8 show a slight increase in explanatory power obtained by adding the four internal capacity factors to the first model (R^2 in model 1 = 0.089 and R^2 model 2 = 0.142). The exploratory part of the study was carried out to test the effect of these variables in as long as it is open to innovation. According to (Fairchild and MacKinnon, 2009), the hypothesis of moderation is supported if both of the following conditions are met: the coefficient of determination of the second model must be greater than the coefficient of determination of the first model; the interaction term has a significant regression coefficient. The coefficient of this interaction is negative ($\beta = -0.065$) and the coefficient of determination of the second model (0.161) is higher than that of model one.

Furthermore, results in Table 8 shows the interface between learning capacities and openness to business associations. The coefficient of this interface is significant ($\beta = 0.059$) and the coefficient of determination of the second model (0.161) is slightly higher than that of the first model (0.142). Finally, results show the interaction between technoscientific consultants and human resources. The coefficient of this interaction ($\beta = - 0.067$) is negative and the coefficient of determination of the second model (0.161) is slightly higher than that of the first model (0.142). Table 9 shows the summary of the hypothesis.

5. DISCUSSIONS

Innovation is the driving force of economic development and remains a major concern for researchers, managers, owner-managers as well as policymakers. OI is considered a method of overcoming capacity limitations. Thus, this study assesses whether SMEs adopting open innovation achieve better results.

Table 8. Result of the test of the moderation effect between study variables

	Model 1		Model 2	
	Regression Coefficient	Signification	Regression Coefficient	Signification
Degree of openness				
External partners				
CM	.063	.209	.052	.254
SRO	.085**	.005	.085	.120
ORGSI	.052***	.001	.185	.224
External knowledge				
BAPCOB	-.029	.427	-.034	.023
RIBN	.156	.162	.125	.160
RIBN1	-.225	.665	-.041	.638
RIBN2	.187	.213	.117	.082
Internal Capacities				
HR			.032***	.000
FR			-.152	.207
TR			.025**	.003
IR			.053***	.001
Interaction term- RGSI*LC			-.065	.091
Adjusted R^2	.142	.161		
F-statistics	2.506	.008	2.908	.091
Interaction term-BAPCOB *LC			.059	.090
Adjusted R^2	.142		.161	
F-statistics	2.506	.008	2.938	.090
Interaction term- RIBN1 *HR			-.067	.088
Adjusted R^2	.142	.161		
F-statistics	2.506	.008	3.035	.085

$P < 0.01$***; $P < 0.05$**; $P < 0.10$*.

Table 9. Summary of study hypothesis

Hypothesis	Independent Variables	Dependent Variables	Estimate	t-stat	p-value	Results
H_1	Degree of openness to external partners and sources of knowledge	Innovation performance	.052	3.872	***	supported
H_2	Human resource capacity	Innovation performance	.032	4.537	***	supported
H_3	Financial resources	Innovation performance	-.152	2.766	.207	Rejected
H_4	Technological resources	Innovation performance	.025	4.934	**	supported
H_5	Information resources	Innovation performance	.053	2.247	***	supported

$P < 0.01$***; $P < 0.05$**; $P < 0.10$*.

Driven by the results of previous researchers, the study attained its object by taking into account the process which is linked to the use of external partners and access to sources of external knowledge (Chesbrough, 2003; Chesbrough and Di Minin, 2014; Chesbrough, 2006; Lichtenthaler, 2008; Van de Vrande et al., 2009; Gassmann, Enkel, and Chesbrough, 2010; Huizingh, 2011). Review of the literature identified some gaps that led to the development of two research hypotheses presented in the conceptual framework. This allowed highlighting a little-studied component, namely the moderating effect of internal capacities on the relationship between the degree of openness and innovation performance in the specific context of agribusiness SMEs.

Overall, the results show that of the seven factors introduced in the first model of multiple linear regression, only three factors; RIBN2 β=187, p = 0.213, RIBN β=-0.156, p = 0.162 and SRO β=0.085, p = 0.05), has a meaningful explanation of innovation performance at a tolerance threshold less than 10%. The result of the two factors of openness (RIBN, SRO) shows significant evidence on open innovation that SMEs require to make greater use of scientific partners (college, university or government) to innovate. This result supports the findings of (Raymond and St-Pierre, 2010) who mention that the most innovative SMEs work closely with research and teaching organizations. In the same vein, this result joins those of Becheikh, Landry, and Amara (2006) who revealed in their study that openness to research institutions increases innovation performance having a positive significant effect on the degree of openness and innovation. Similarly, this result corroborates with those of Granovetter (1985), Nahapiet and Ghoshal (1998), who explain that collaborations with universities allow companies to share the knowledge necessary for the realization of R & D and innovation. High-tech companies introducing innovation in products and processes are more likely to rely more on sources of knowledge related to R&D.

Moreover, this result confirms once again the study of Fontana, Geuna, and Matt (2006) who also reported the positive effect of R&D collaboration with public research institutions and the importance of openness to universities to generate new ideas and successfully finalize innovation activities. Gökalp, Şener, and Eren (2017) argues that companies in transition must fundamentally adopt the technology practices of Industry 4.0. Because it plays an important role in the connection between R & D, innovation and automated systems. Industry 4.0 (fourth industrial revolution) enables everything to communicate directly with the company's IT systems to meet customers' demand. Optimized decision-making allows information to flow seamlessly in areas such as sales, resource productivity, flexibility, and efficiency. According to these researchers, openness to these sources of external knowledge helps to transfer important scientific and technical knowledge. In addition, in the agri-food sector, these authors emphasize that universities help businesses comply with government regulations.

Although this result shows that partners from the scientific world (RIBN, SRO) are the majority in number and explain a significant contribution to performance innovation, it emerges from this study that business consultants play a critical role in open innovation. Indeed, it is the factor with strong significant ($p < 0.001$) on innovation performance with 85% of SMEs that collaborate with partners. This result corroborates that of Raymond and St-Pierre (2010) who find that collaborations with the business community have a significant impact on innovation performance compared to organizations technology. In addition, the result agrees with those acquired by Laursen and Salter (2006) and those of Zhang et al. (2018) who have already emphasized the importance of these sources of external knowledge of consultants for the innovation activities of the companies. This result also confirms those of Cruz-Gonzalez, Lopez-Saez, and Navas-Lopez (2015) and Spencer (2003) who mention that companies looking for new Knowledge combinations often require interaction with different actors external to organizations, including consultants. In general, two explanations can be advanced regarding the first hypothesis. First, it appears that opening on business consultants (RIBN2) and research institutes for business needs (RIBN) as well as specialized research organizations for Technical Requirements (SRO) promotes innovation performance in the context of SME surveyed in this study. In other words, SMEs that are most innovative are those that maintain close relations with their main external partners to innovate. The results partially confirm the first hypothesis where certain factors in innovation (RIBN and SRO) significantly influence performance innovation.

The research hypothesis; H_2 to H_5 assumes that internal capabilities have a positive moderating impact on the relationship between the degree of openness and performance innovation. The result shows that comparing the factors in model 1 and 2, the addition of four factors of the moderator variable internal capabilities and learning abilities (LC) indicate significant variations in OI and firm performance. Only one of these four factors of the internal capacities seems to have no effect on performance innovation H_3 ($p > 0.05$). Thus, H_2, H_4, and H_5 are validated with exception of H_3 (see Table 9). Nonsignificant results in support of financial resources (H_4) could be due to limited seed capital associated with SMEs start-ups (Barron, Hultén, and Hudson, 2012). The significant effect of internal capacity factors seeks to achieve a more exploratory component by considering internal capacities as a variable antecedent to open innovation. In other words, it is examined whether the presence of adequately developed internal capacities within the SMEs stimulates the degree of openness, which in turn can have an impact on the performance innovation (Greco, Grimaldi & Cricelli, 2015) as validated in the first hypothesis.

Statistical results lead to an interpretation of the moderation that a strong openness to support organizations for innovation accompanied by developed learning capabilities are associated with a high innovation performance (Zhang et al., 2018), while a low openness to support organizations accompanied by poorly developed learning abilities leads to dismal performance innovation (Oltra, Flor, and Alfaro, 2018). The second moderation whose interaction is composed of business associations and learning abilities is characterized by a positive coefficient interaction ($\beta = 0.059$). Statistical results lead to introspect moderation as follows. A strong openness to business associations accompanied by developed learning capabilities is associated with high-performance innovation, while a weak opening on business associations accompanied by poorly developed learning abilities are associated with a low-performance innovation.

The interaction of technoscientific consultants and human resources is characterized by a negative interaction coefficient ($\beta = - 0.067$). The results lead to an interpretation of the moderation as follows. A strong openness to technoscientific consultants accompanied by developed human resources are associated with high-performance due to the heterogeneous behavior of firm innovation strategy (Ahn et al., 2016). Considering the dynamic and intricate nature of innovation that is characterized by diversified resources (human, financial, technological and informational), and multiple collaborations with varied external knowledge (Fakhreddine, Amara, and Landry, 2012), its evidence that every SME is singular in the sense that it adopts business practices and commits resources according to its own strategic objectives in terms of innovation. Thus, from the results, the second hypothesis is verified.

5.1. Study Implications

The study theoretical implication advances the literature in OI research centered on the perspectives of agribusiness enterprise in developing countries. In practical terms, this study found that although OI brings many benefits to agribusiness through various applications; its implementation in rural areas is a challenge that limits business growth. Thus, government policy and support programs should facilitate OI in terms of infrastructure and resources to boost economic development and food security. Furthermore, government policy should endeavor to facilitate different forms for technical skills and financial incentive for SMEs. This could be linked to issues of training and facilitating the process of OI as a prerequisite for advancing internal capabilities. In addition, the linkage between the research institutions and the SMEs need to be strengthened.

The use multidimensional approach of integrating internal factors (internal capacities) and external partners as bases for outward information should be enhanced. There is a need for continuous interactions that entail interactive, mutual learning processes, with feedbacks that also flow back from the end user to the partners. Furthermore, entrepreneurs should advance the creation of new instruments for measurement of the degree of openness in innovation through the use of external partners' knowledge and ideas. This collaboration can be enhanced through conferences, consortia, symposia and consultation from the various industries and academia. This collaborative and partnerships aspect can be useful for fostering innovation activities in SMEs, especially in a growing business environment that is globally competitive.

5.2. Limitations and Perspective for Future Research

While the results of the study deliver a valuable understanding of the interdependence among the study variables, this paper had limitations that create an avenue for future study. First, the study-selected respondents based on the sampling technique that has disadvantages with respect to the generalizability of the results, though the technique was appropriate for the study due to the nature of the information collected from SMEs. Furthermore, the study used semi-structured questionnaires as a data collection instrument, which has a limitation on the construct validity (Avolio, Yammarino, and Bass, 1991). The questionnaires gather information from the manager and staff who work for the firm, but innovation and firm performance changes over time.

In addition, the paper did not cover other interactive factors that relate to employees' and entrepreneur's characteristics and attitudes that influence OI. The research focused primarily on the incoming process of open innovation while the other processes (outgoing process) have not been put into consideration. Variables relating to the degree of openness in innovation can be expanded by taking into account other external partners such as suppliers, government departments and agencies. Future research can benefit from applying a longitudinal survey to capture the impact and relationships between OI, entrepreneur's strategic capacity, and firm performance. Using this research design would produce validated results. Similarly, undertaking a comparative study with agribusinesses in urban areas would give more insight into the comparison between SMEs operating in a different location but with some common features in Kenya.

In conclusion, the main aim of this study was to analyze the impact of the entrepreneur's open innovation on firm performance. The goal of OI in agribusiness enterprises is to develop internal capabilities of the firm to meet the country food security objectives. The results indicate a positive relationship between OI and firm performance. Furthermore, the entrepreneur's strategic behavior influences the effectiveness of OI that has an impact on agribusiness performance. However, programs to facilitate and increase consultants' interventions within the SME sector and initiatives that strengthen partnerships between institutions of research and SMEs limit the OI to agribusiness enterprises in developing countries. Thus, government policy should focus on building a web platform to exchange useful knowledge on innovation activities among SME managers to update their innovation capabilities. The results of this study are significant to agribusiness enterprises, education practitioners, and policymakers in identifying appropriate OI mechanisms that promote SMEs capacity and sustainable agribusiness sector.

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Information Resources Management Journal
Volume 32 • Issue 4 • October-December 2019

Understanding the Acceptance and Use of M-Learning Apps by Entrepreneurs:

An Application of the Social-Cognitive and Motivational Theories

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ABSTRACT

This study is designed to examine factors influencing the acceptance of m-learning apps by entrepreneurs. The constructs used to develop the proposed model were drawn from the social cognitive and motivational theories. The model was validated using 218 valid responses from entrepreneurs in South Africa. The results showed that both intrinsic (i.e. perceived enjoyment) and extrinsic (i.e. perceived usefulness and social influence) motivational factors had a direct positive influence on the behavioral intentions to adopt m-learning apps. Also, perceived usefulness, which showed the strongest direct influence on behavioral intentions, was directly influenced by outcome expectancy, and indirectly influenced by self-efficacy. The study also evaluated the outcomes of use behavior. For one, entrepreneurs who used m-learning apps were more likely to recommend the m-learning apps to others. Moreover, use behavior was shown to have a significant positive influence on entrepreneurial self-efficacy.

KEYWORDS

Entrepreneurs, Extrinsic Motivation, Intrinsic Motivation, M-Learning, Social Cognitive Theory

1. INTRODUCTION

Advances in mobile technologies over the years have opened up a wide range of services and information that can be accessed through different kinds of mobile applications for use in various domains. One such domain that has seen unprecedented improvements is the mobile learning (m-learning) domain. As such, there has been increasing interest from researchers in understanding the acceptance of m-learning applications (Al-Emran, Mezhuyev, Kamaludin, 2018; Milošević, Živković, Manasijević & Nikolić, 2015). M-learning can be broadly defined as the use of mobile technologies to acquire knowledge and skills (Liu, Li & Carlsson, 2010). M-learning is quite popular because it provides several benefits to users including portability, ubiquity and mobility (i.e. learning not constrained by time and location), increased engagement with learning content, ability to enhance knowledge retention, cost-effectiveness, and the rapid development of the capabilities of mobile devices (Milošević et al., 2015; Peng, Su, Chou & Tsai, 2009).

DOI: 10.4018/IRMJ.2019100103

Despite the benefits and growing capabilities of m-learning applications (henceforth referred to simply as m-learning apps), many researchers have argued that much is still not known about the factors that influence the acceptance of m-learning apps (Al-Emran et al., 2018; Liu et al., 2010; Milošević et al., 2015; Sabah, 2016). This could possibly be explained by the over-reliance on the technology acceptance model (TAM) as the majority of m-learning studies to date have focused on the TAM as their fundamental theoretical model (Al-Emran et al., 2018; Poong, Yamaguchi & Takada, 2017; Sánchez-Prieto, Olmos-Migueláñez & García-Peñalvo, 2017). In fact, continuous validation of the TAM in the m-learning context has provided mixed findings. For example, while some researchers have found ease of use to positively influence m-learning adoption (Poong et al., 2017), the association was non-significant in other studies (Liu et al., 2010). As such, instead of simply extending the TAM with other constructs as suggested in prior studies (Al-Emran et al., 2018), new insights on the factors that influence m-learning acceptance might be gained by developing and testing other theoretical models. This is particularly important as Benbasat and Barki (2007) argued that over-reliance on the TAM in any domain might put blinders on researcher's abilities to unearth other valuable constructs, theories, and models that could explain technology acceptance in the domain (i.e. m-learning in the context of the present study). Additionally, although m-learning apps are widely used outside of academia (Liu et al., 2010), the systematic review by Al-Emran et al. (2018) showed that many of the prior studies on m-learning adoption have mostly focused on students. As such, it is imperative to also evaluate m-learning acceptance by other groups of users. Lastly, existing technology acceptance measurements have been criticized for not considering outcome factors by examining whether or not the use of the adopted technologies provide any known benefits to the users (Oliveira, Thomas, Baptista & Campos, 2016). The above discussion clearly suggests the existence of important gaps that need to be addressed in the m-learning adoption literature.

Against the backdrop of the foregoing arguments, the present study aims to make three main contributions. Firstly, the study develops and presents a new model for acceptance of m-learning apps using the social cognitive and motivational theories. Secondly, the study shifts away from the traditional evaluation of student's acceptance of m-learning apps and focuses on the acceptance of these apps by entrepreneurs. The focus on entrepreneurs is motivated by the widely acknowledged contribution of entrepreneurship in today's world (Maritz & Brown, 2013; Von Graevenitz, Harhoff & Weber, 2010) and the fact that entrepreneurs require continuous self-directed learning to achieve sustained success in their businesses (Erzetic, 2008). As such, entrepreneurs can benefit from the portability, ubiquity, and mobility of m-learning apps to continuously improve their knowledge and skills, thus making them a valuable user group for m-learning apps. Lastly, by focusing on entrepreneurs, the present study includes an outcome variable in the model by examining how the use of m-learning apps influenced entrepreneurial self-efficacy.

The rest of this study is structured as follows. Next, the paper presents the theoretical background, highlighting the key theories used in the development of the model. Afterward, the research model and the development of the hypotheses are presented. Following that is a presentation of the research methodology and data analysis. Lastly, the discussion and conclusions are presented.

2. THEORETICAL BACKGROUND

2.1. Social Cognitive Theory (SCT)

The SCT postulates that human behavior is determined by social and psychological or personal factors. Basically, the SCT focuses on analyzing how cognitive processes (i.e. feelings and thoughts) and social interactions determine the behavioral actions that an individual will take. Many researchers share the view that the SCT is one of the most powerful theories for explaining human behavior (Ifinedo, 2017; Rana & Dwivedi, 2015). As such, the SCT has been widely used to test human behavior in different domains, including the use of information systems. In the present study, the focus will be on the psychological or personal factors of the SCT, or more specifically, on the perceived self-efficacy and personal outcome expectancy (henceforth referred to simply as outcome expectancy). Self-efficacy refers to an individual's judgment of his/her ability to successfully execute the courses of actions needed to complete a given task or to achieve certain goals, while outcome expectancy refers to the expectations of benefits or rewards that an individual expects to attain from engaging in a given behavior (Ifinedo, 2017; Rana & Dwivedi, 2015). These factors are selected in the present study because of their theoretical association with the extrinsic and intrinsic motivational factors that are likely to influence user adoption of m-learning apps.

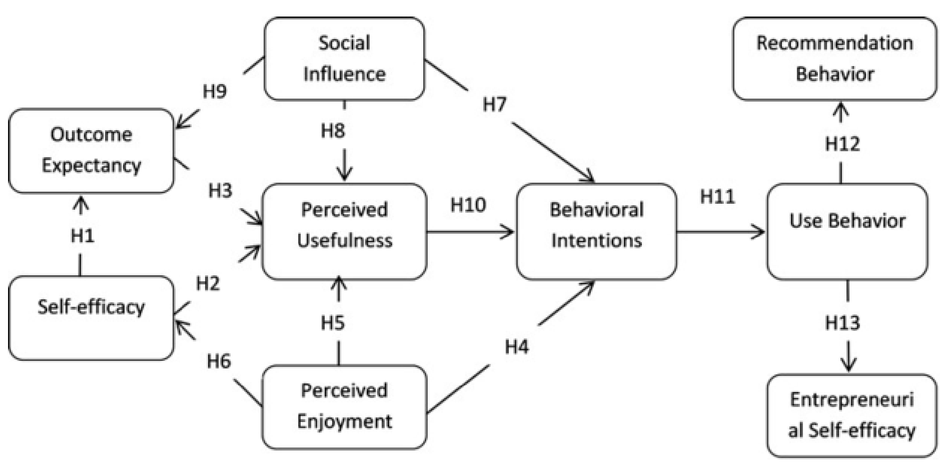
2.2. Intrinsic and Extrinsic Motivation

The cognitive evaluation theory classifies emotions into two main subsystems, namely, intrinsic and extrinsic motivation. This view has also been supported in information systems literature as researchers over the years have argued that a user's decision regarding the adoption and use of an information system is often influenced by the user's extrinsic and intrinsic motivational disposition (Ifinedo, 2017; Kim et al., 2014). Intrinsic motivation focuses on the fun/pleasure associated with the use of a given system while extrinsic motivation embodies the potential positive outcomes that an individual can attain from using the system (Ifinedo, 2017; Kim, Kang & Jo, 2014). Prior information system studies have established perceived enjoyment as a valuable exemplification of intrinsic motivation (Kim et al., 2014), while perceived usefulness and social influence have been argued to be valuable examples of extrinsic motivation (Ifinedo, 2017; Kim et al., 2014; Yoo, Han & Huang, 2012). Perceived enjoyment has been broadly defined as the extent to which an individual can perceive the use of a given system to be pleasurable in its own right, exclusive of other performance outcomes (Thong et al., 2006). Perceived usefulness encompasses the extent to which an individual believes that using a given technology will improve his/her productivity. Social influence refers to an individual's perception regarding the extent to which people important to him/her would support their use of a given technology (Venkatesh, Thong & Xu, 2012). These three factors are adopted in the present study to represent the intrinsic and extrinsic motivational dispositions that influence the acceptance and use of m-learning apps.

3. RESEARCH MODEL AND DEVELOPMENT OF HYPOTHESES

Figure 1 presents the research model. The present study combines constructs from the social cognitive and motivational theories to develop and test a model for m-learning adoption. Consistent with prior

Figure 1. Theoretical model



literature on the role of motivation in technology adoption (Ifinedo, 2017; Kim et al., 2014; Yoo, Han & Huang, 2012), the present study posits that intrinsic (i.e. perceived enjoyment) and extrinsic (i.e. perceived usefulness and social influence) motivational factors have a direct influence on the behavioral intentions to adopt m-learning apps. Additionally, constructs from the SCT play a vital role in influencing perceived usefulness (Fernández-Cardador, Hernández-García & Iglesias-Pradas, 2014; Ifinedo, 2017; Rana & Dwivedi, 2015), while social influence and perceived enjoyment also influence perceived usefulness directly and indirectly via the SCT constructs (Poong et al., 2017; Rana & Dwivedi, 2015; Yi & Hwang, 2003). Additionally, as evidenced in prior studies (Oliveira et al., 2016; Venkatesh et al., 2012; Verkijika, 2018) behavioral intentions will lead to use behavior which in turn will lead to recommendation behavior. Since this study focused on entrepreneurship m-learning apps, it was also possible to add another construct, namely entrepreneurial self-efficacy. Entrepreneurial self-efficacy refers to an individual's belief in his/her ability to start and run a business successfully (Shinnar, Hsu & Powell, 2014). The addition of this construct enhances the contribution of the theoretical model as some researchers have emphasized that technology acceptance models need to include more innovative constructs such as examining whether or not the acceptance and use of a given technology will provide any positive outcomes for the users (Oliveira et al., 2016).

3.1. Self-Efficacy

Generally, people who have a high level of self-efficacy in a given domain are often more inclined to engage in activities in that domain. As such, their appraisal of activities in such a domain is often more positive than those with low levels of self-efficacy. This has been supported by existing evidence showing that high levels of self-efficacy associated with the use of a given technology is often associated with favorable perceptions and expectations regarding the use of the technology (Ifinedo, 2017; Rana & Dwivedi, 2015). For example, researchers have shown that high self-efficacy is significantly associated with positive views regarding the perceived usefulness of a given system (Lee & Mendlinger, 2011). Additionally, individuals with a high self-efficacy in a given activity often tend to expect more satisfactory outcomes/rewards from an activity than those with low levels of self-efficacy (Ifinedo, 2017; Lu, Mao, Wang & Hu, 2015; Rana & Dwivedi, 2015). Consequently, in the context of this study, it is predicted that individuals with a high level of self-efficacy regarding the use of m-learning apps will be more inclined to have positive expectations from the use of m-learning apps (i.e. outcome expectancy), and also hold positive views regarding their perceived usefulness. Thus, it is hypothesized that:

H1: Perceived self-efficacy will have a significant positive influence on outcome expectancy.
H2: Perceived self-efficacy will have a significant positive influence on perceived usefulness.

3.2. Outcome Expectancy

According to the SCT, people are generally more inclined to engage in behaviors from which they expect some sort of reward or gain (Lu & Hsiao, 2007). In the context of information systems, researchers have shown that individuals who expect to reap some form of benefit from a given technology were more likely to adopt and use the technology (Ifinedo, 2017; Rana & Dwivedi, 2015). Consequently, such individuals will generally be more inclined to have a favorable appraisal of the perceived usefulness of the technology. This has been supported by several studies that have shown a significant positive influence of outcome expectancy on perceived usefulness (Fernández-Cardador et al., 2014; Ifinedo, 2017). Thus, in the context of this study, it is expected that individuals who expect to benefit from using an m-learning app will be more inclined to rate such apps as useful. Based on this argument, the following hypothesis is proposed.

H3: Outcome expectancy will have a significant positive influence on perceived usefulness.

3.3. Perceived Enjoyment

Perceived enjoyment is often considered as a valuable intrinsic motivational factor that pushes individuals to use a given technology (Kim et al., 2014). As such, individuals who perceive a given technology to be pleasurable to use are more inclined to adopt and use the technology. This view has been supported by several studies that have established the existence of a significant positive influence of perceived enjoyment on the intentions to adopt a given technology (Teo & Noyes, 2011) as well the continued use of the technology (Thong et al., 2006). This is because individuals are always inclined to engage in activities from which they derive some form of enjoyment. Additionally, some researchers (Poong et al., 2017; Teo & Noyes, 2011; Yi & Hwang, 2003) have shown that technological systems that are perceived to be enjoyable are also considered to be more useful. This could result from the fact that enjoyable systems are considered to be easy to use, which is a key determinant of perceived usefulness (Teo & Noyes, 2011). Lastly, based on the view that the affective state of an individual is a vital source of self-efficacy beliefs, Yi and Hwang (2003) argued and empirically showed that individuals who perceived the use of a given technological system to be enjoyable were more likely to express greater confidence in their ability to successfully execute the actions needed to complete a given task on the system (i.e. self-efficacy). Following the above discussion, the following hypotheses are proposed:

H4: Perceived enjoyment will have a significant positive influence on behavioral intentions.
H5: Perceived enjoyment will have a significant positive influence on perceived usefulness.
H6: Perceived enjoyment will have a significant positive influence on self-efficacy.

3.4. Social Influence

Prior research emphasizes that the suggestions from significant others (e.g. friends and family) always play a vital role in the decisions they take regarding the use of a given technology (Rana & Dwivedi, 2015). This is because humans as social beings are generally susceptible to influences from their social groups such as friends, colleagues or family members. More specifically, individuals might tend to consider the information received within their social group as some evidence of reality from which they judge a given technology and thus make adoption decisions based on such information, or they might simply have a desire to conform to the expectations of significant others regarding the use of a given technology (Zhang, Fam, Goh & Dai, 2018). This view has been supported by several studies that have provided empirical evidence of the positive influence of social influence on technology adoption (Rana & Dwivedi, 2015; Venkatesh et al., 2012; Verkijika, 2018). Additionally, individuals always tend to believe that a system is useful and beneficial to them when significant others approve of their use of the system. This is because the social expectation that one should consider adopting a given technology ultimately enhances the individual’s positive appraisal of the technology’s potential value. This view has been supported by several studies that have shown a significant positive influence of social influence on perceived usefulness (Koenig-Lewis et al., 2015; Poong et al., 2017) and outcome expectancy (Rana & Dwivedi, 2015). As such, the following hypotheses are proposed:

H7: Social influence will have a significant positive influence on behavioral intentions.
H8: Social influence will have a significant positive influence on perceived usefulness.
H9: Social influence will have a significant positive influence on outcome expectancy.

3.5. Perceived Usefulness

Perceived usefulness is one of the extrinsic motivational factors that have been widely touted as a key determinant of technology adoption (Sánchez & Hueros, 2010). Researchers have argued that individuals will be more inclined to use a technology for carrying out their activities if they believe that it will be a useful tool for attaining their goals (Mohammadi, 2015). This view has been supported empirically with several studies that have shown a significant positive influence of perceived usefulness on behavioral intentions to adopt a given technology (Liu & Huang, 2015; Mohammadi, 2015; Poong et al., 2017). As such, the following hypothesis is proposed:

H10: Perceived usefulness will have a significant positive influence on behavioral intention

3.6. Behavioral Intentions

Behavioral intention in the context of the present study can be broadly defined as an individual's subjective probability of using a given m-learning app (Verkijika, 2018). Prior research has argued that an individual's decision to accept a given technology is often directly influenced by their behavioral intention to use the technology (Venkatesh et al., 2012). This view has been empirically supported by prior studies that have established the significant influence of behavioral intentions on use behavior (Venkatesh et al., 2012). Thus, the following hypothesis is proposed.

H11: Behavioral intention will have a significant positive influence on use behavior.

3.7. Consequences of Use Behavior

The present study proposed two important consequences of the use of entrepreneurship m-learning apps namely recommendation behavior and entrepreneurial self-efficacy. The recommendation of a technology is a more general consequence of technology use while entrepreneurial self-efficacy is more specific to the context of the present study as it is seen as a direct consequence of using entrepreneurship m-learning apps. The recommendation behavior associated with an information system refers to the willingness shown by a user of the system to encourage others to use the system. Generally, it is expected that individuals who use a given system will be the most likely candidates to recommend it to others (Verkijika, 2018). Thus, it is hypothesized that:

H12: Use behavior will have a significant positive influence on recommendation behavior.

With regards to entrepreneurship m-learning apps, it can be expected that entrepreneurs who use these apps will have a higher level of entrepreneurial self-efficacy. Prior evidence suggests that entrepreneurship education enhances entrepreneurial self-efficacy (Von Graevenitz et al., 2010; Maritz & Brown, 2013; Shinnar et al., 2014). As such, the entrepreneurial knowledge gained through entrepreneurship m-learning apps can play a vital role in enhancing entrepreneurial self-efficacy. Hence, the following hypothesis is proposed:

H13: Use behavior of entrepreneurship m-learning apps will have a significant positive influence on entrepreneurial self-efficacy.

4. METHODOLOGY

In order to evaluate the proposed model, a survey methodology was used to gather data from entrepreneurs. Using Daniel Soper's A-priori sample size calculator for structural equation models, it was observed that the recommended sample size to test the proposed model was 184. As such, using convenience sampling, data was gathered from 218 entrepreneurs in South Africa. Convenience sampling was used as there was no list of entrepreneurs available to the researcher while South Africa was chosen because of easy access to respondents. All the measurements for the constructs used in the model, except for entrepreneurial self-efficacy were adapted from prior studies that focused on the adoption of different forms of information systems (Ifinedo, 2017; Kim et al., 2014; Rana & Dwivedi, 2015). Sample items included: "If I use m-learning apps, I will increase my effectiveness" (outcome expectancy), "I have confidence in my ability to use m-learning apps" (self-efficacy), "People who are important to me think that I should use m-learning apps" (social influence), "M-learning apps are useful tools for enhancing my performance in managing my business" (perceived usefulness), "I would have fun using m-learning apps" (perceived enjoyment), and "I intend to use m-learning apps" (behavioral intentions). All these items were measured on a five-point scale ranging from 1 (strongly disagree" to 5 (strongly agree). The items for measuring entrepreneurial self-efficacy were adopted from the entrepreneurship literature using the four-item scale developed by Zhao, Hills, and Seibert (2005) in which respondents were asked to rate their level of confidence in completing several entrepreneurial tasks on a five-point scale ranging from 1 (no confidence) to 5 (complete confidence). Additionally, the questionnaire also gathered data on the demographic profiles of the respondents (Table 1). All the respondents had a smartphone and thus were considered as potential users of entrepreneurship m-learning apps.

From Table 1, it is observed that males comprised 53.2% of the sample while females made up 46.8%. Also, the majority of the respondents were between the age group of 31 – 40 years while many of the respondents had at least an undergraduate degree (56.8%).

5. DATA ANALYSIS

The partial least square (PLS) approach of structural equation modeling (SEM) was used to test the hypothesized associations using the SmartPLS 3.0 software (Ringle, Wende & Becker, 2015). The reliability and validity of the constructs were assessed in the measurement model while the hypotheses were assessed in the structural model using bootstrapping with 5000 sub-samples. Reliability was assessed using Cronbach's alpha and composite reliability whereby, values above 0.7 in each case were considered to demonstrate an adequate level of reliability (Hair, Hult, Ringle & Sarstedt, 2016). From the information in Table 2, it is observed that the Cronbach's alpha and composite reliability

Table 1. Descriptive statistics

Demographic Information		
Gender	**#**	**%**
Male	116	53.2
Female	102	46.8
Age	**#**	**%**
Less than 25 years	38	17.4
25-30 years	67	30.7
31-40years	92	42.2
Above 40 years	21	9.6
Education	**#**	**%**
High school diploma or below	35	16.1
Higher education diploma	59	27.1
Undergraduate degree	96	44.0
Postgraduate (above degree)	28	12.8

Note: # is the frequency, while % is the percentage.

Table 2. Reliability and convergent validity

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intentions (BI)	0.890	0.932	0.820
Entrepreneurial Self-efficacy (ESE)	0.872	0.913	0.725
Outcome Expectancy (OE)	0.912	0.945	0.850
Perceived Enjoyment (PE)	0.894	0.934	0.825
Perceived Usefulness (PU)	0.907	0.942	0.843
Recommendation Behavior (RB)	0.831	0.921	0.854
Self-efficacy (SE)	0.924	0.963	0.929
Social Influence (SI)	0.930	0.955	0.877
Use Behavior (UB)	0.859	0.899	0.642

values are all above 0.7 thus indicate that all constructs in the proposed model demonstrated an acceptable level of reliability.

With respect to validity, convergent validity was assessed using the construct's average variance extracted (AVE) based on the recommendation that a construct's AVE should be above 0.5 (Hair et al., 2016). As shown in Table 2, the AVE values ranged from 0.642 to 0.929, is above the recommended value of 0.5, thus confirming the convergent validity of the constructs. Divergent validity was assessed using the Heterotrait-Monotrait Ratio (HTMT) which some researchers have argued that it provides a more adequate measure of discriminant validity than the commonly used Furnell-Lacker criteria (Henseler, Ringle & Sarstedt, 2015; Verkijika & De Wet, 2018). The SmartPLS software computes the HTMT values by assessing the ratio of the absolute correlations of indicators across constructs measuring different phenomena relative to the absolute correlations of the indicators within the same construct. This ratio is computed for each pair of constructs to determine how well the constructs differ from each other. Generally, HTMT values below 0.9 indicate acceptable levels of discriminant validity, even though some authors encourage a more conservative value of 0.85 (Hair et al., 2016; Verkijika & De Wet, 2018). From Table 3, it is observed that all the HTMT values are below the conservative value of 0.85. As such, all the constructs are considered to demonstrate acceptable levels of discriminant validity.

Table 3. Heterotrait-Monotrait ratio (HTMT)

	BI	ESE	OE	PE	PU	RB	SE	SI
ESE	0.669							
OE	0.715	0.643						
PE	0.528	0.835	0.489					
PU	0.793	0.617	0.672	0.493				
RB	0.531	0.582	0.464	0.437	0.508			
SE	0.625	0.680	0.843	0.499	0.624	0.401		
SI	0.588	0.472	0.334	0.349	0.370	0.487	0.272	
UB	0.725	0.618	0.579	0.410	0.571	0.631	0.465	0.412

Figure 2 (i.e. structural model) presents the beta coefficients (β) and the significance of the paths along with the variance explained (R^2-value) for each dependent variable in the model. Non-significant paths are indicated in dashed lines. The model accounted for 61.9% variance in behavioral intentions. For the factors explaining behavioral intention, perceived usefulness had the highest influence (β = 0.551, $p < 0.01$), followed by social influence (β = 0.308, $p < 0.01$) and perceived enjoyment (β = 0.129, $p < 0.05$) respectively.

Also observed in Figure 2 is that behavioral intentions accounted for 40.8% variance in use behavior (β = 0.639, $p < 0.01$) which in turn accounted for 29.1% variance in recommendation behavior (β = 0.539, $p < 0.01$) and 29.2% variance in entrepreneurial self-efficacy (β = 0.540, $p < 0.01$). Likewise, perceived enjoyment accounted for 20.7% variance in self-efficacy (β = 0.455, $p < 0.01$) while self-efficacy (β = 0.743, $p < 0.01$) and social influence (β = 0.122, $p < 0.01$) accounted for 61.3% variance in outcome expectancy. The model also accounted for 44% variance in perceived usefulness, however, only outcome expectancy (β = 0.350, $p < 0.01$) and perceived enjoyment (β = 0.159, $p < 0.05$) showed a significant direct influence on perceived usefulness, while the direct effects of social influence (β = 0.133, $p > 0.05$) and self-efficacy (β = 0.194, $p > 0.05$) were not supported. This is contrary to the expectations of hypothesis H2 and H8 which suggested the existence of a significant positive influence of self-efficacy (H2) and social influence (H8) on perceived usefulness. Nonetheless, it is imperative to indicate that the total indirect effect of both social influence (β = 0.043, $p < 0.05$) and self-efficacy (β = 0.260, $p < 0.01$) on perceived usefulness (i.e. via outcome expectancy) was significant.

In total, only two (i.e. H2 and H8) out of the 13 hypothesized associations were non-significant. A summary of the outcome of all the hypothesized associations is presented in Table 4.

6. DISCUSSION

The present study examined the adoption and use of entrepreneurship m-learning apps by small business owners using relevant constructs from the social cognitive and motivational theories. The proposed model presented 13 hypotheses of which only two (i.e. H2 and H8) were not supported. It was observed that self-efficacy had a significant influence on outcome expectancy (H1), supporting the view that individuals with a high level of self-efficacy in a given domain will tend to expect more satisfactory outcomes or rewards as shown in prior studies (Ifinedo, 2017; Lu et al., 2015; Rana & Dwivedi, 2015). Self-efficacy, however, failed to significantly influence perceived usefulness as

Figure 2. Structural model

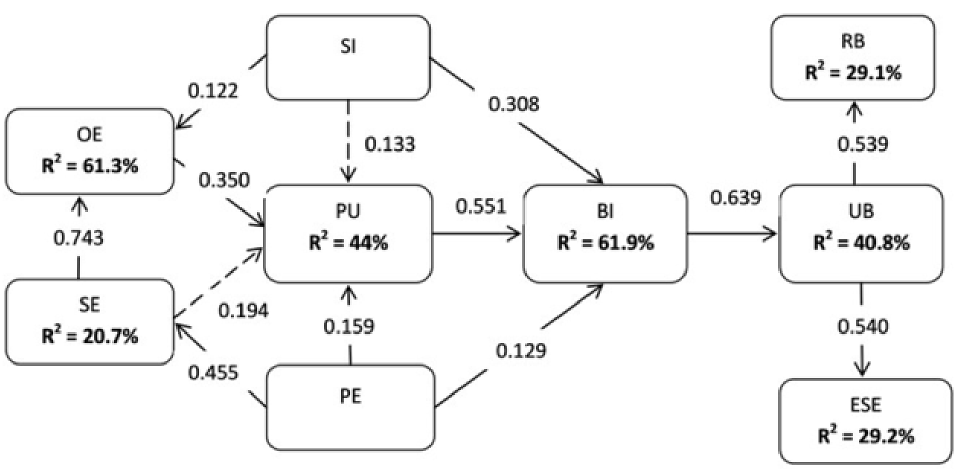


Table 4. Outcome of hypotheses

Hypotheses	Constructs' Relationship	Standardized Path Coefficient	Critical Ratio	Significance (p)	Hypothesis Supported (Yes / No)
H1	SE → OE	0.743**	15.161	p = 0.000	Yes
H2	SE → PU	0.194	1.775	p = 0.076	No
H3	OE → PU	0.350**	3.259	p = 0.001	Yes
H4	PE → BI	0.129*	2.453	p = 0.014	Yes
H5	PE → PU	0.159*	2.398	p = 0.017	Yes
H6	PE → SE	0.455**	7.426	p = 0.000	Yes
H7	SI → BI	0.308**	5.685	p = 0.000	Yes
H8	SI → PU	0.133	1.935	p = 0.053	No
H9	SI → OE	0.122**	2.694	p = 0.007	Yes
H10	PU → BI	0.551**	13.489	p = 0.000	Yes
H11	BI → UB	0.639**	19.597	p = 0.000	Yes
H12	BU → RB	0.539**	10.942	p = 0.000	Yes
H13	BU → ESE	0.540**	13.489	p = 0.000	Yes

Note: **p < 0.01; *p < 0.05

postulated in hypotheses H2. Some researchers have also failed to establish the significant positive influence of self-efficacy on perceived usefulness (Ifinedo, 2017). The influence of outcome expectancy on perceived usefulness was significant (H3), suggesting that individuals who expect to gain some rewards from a given technology will be more likely to provide a positive appraisal of its perceived usefulness. This finding has also been supported by several studies (Fernández-Cardador et al., 2014; Ifinedo, 2017).

Perceived enjoyment was found to have a significant positive influence on behavioral intentions (H4), perceived usefulness (H5) and self-efficacy (H6). This suggests that individuals who perceive a given technology to be enjoyable are more likely to provide a favorable appraisal of its usefulness, believe in their ability to use it, and adopt it. These views have been supported by several studies (Poong et al., 2017; Teo & Noyes, 2011; Yi & Hwang, 2003). Social influence was found to have a significant positive influence on behavioral intentions (H7) and outcome expectancy (H9), but not on perceived usefulness (H8). This suggests that significant others play a vital role in influencing how people perceived the expected rewards/benefits of using a given technology as well as their desire to adopt and use it. This view has been supported by several studies that have also established a significant positive influence of social influence on behavioral intentions (Rana & Dwivedi, 2015; Venkatesh et al., 2012; Verkijika, 2018) and outcome expectancy (Rana & Dwivedi, 2015). However, the findings are inconsistent with studies that showed a positive influence of social influence on perceived usefulness (Koenig-Lewis et al., 2015; Poong et al., 2017). Instead, the present study suggests that the influence of social influence on perceived usefulness is rather indirect through the role of outcome expectancy.

Perceived usefulness was shown to have a significant positive influence on behavioral intentions (H10), suggesting that individuals will have a high probability of adopting a technology when they believe it will be useful to attain their goals. This supports the findings from prior studies (Liu & Huang, 2015; Mohammadi, 2015; Poong et al., 2017) that have also shown the existence of a significant positive influence of perceived usefulness on behavioral intentions. Also, behavioral intentions had a significant positive influence on use behavior (H11) which in turn had a significant positive influence on recommendation behavior (H12) and entrepreneurial self-efficacy (H13). This supports the view that behavioral intentions are an important determinant of technology use behavior (Venkatesh et al., 2012), and that those who use a given technology will be most likely to recommend it to others (Verkijika, 2018). Lastly, the study supports that view that entrepreneurship education enhances entrepreneurial self-efficacy (Maritz & Brown, 2013; Shinnar et al., 2014; Von Graevenitz et al., 2010) by showing that the use of entrepreneurship m-learning apps has a significant positive influence on entrepreneurial self-efficacy.

6.1. Implications for Research and Practice

The present study combined the social cognitive and motivational theories to develop a model for explaining the user acceptance of m-learning apps. In particular, the study focused on the entrepreneurial community by examining entrepreneurs' propensity to accept and use entrepreneurship m-learning apps. By focusing on a specific user group, it was also possible to extend the model with novel constructs relating to the user group. In this case, the model further evaluated how the use behavior of entrepreneurship m-learning apps influenced entrepreneurial self-efficacy. It was observed that the model significantly explained entrepreneurial self-efficacy. For researchers, this study provides a good basis for refining existing models when applied in specific context to be able to add new variables that could further demonstrate the need for users to accept and use the given technology. The findings of the study contribute to the literature on the acceptance of m-learning apps.

The practical implications are threefold. Firstly, the importance of entrepreneurship in today's economy has been widely recognized, thus necessitating the need for enhancing entrepreneurial self-efficacy. Several studies have shown that entrepreneurship education is vital for improving entrepreneurial self-efficacy (Graevenitz et al., 2010; Maritz & Brown, 2013; Shinnar et al., 2014). However, these studies have mostly been focused on classroom-based entrepreneurship education programs. However, the present study showed that entrepreneurial self-efficacy could also be improved by the use of entrepreneurship m-learning apps. As such, initiatives aimed at improving entrepreneurial self-efficacy can focus on encouraging individuals to adopt and use entrepreneurship m-learning apps.

Secondly, in order to promote the acceptance of entrepreneurship m-learning apps, both intrinsic (i.e. perceived enjoyment) and extrinsic (i.e. perceived usefulness and social influence) motivational factors should be considered. With respect to intrinsic motivation, it is vital to promote the enjoyable parts of using the entrepreneurship m-learning apps. M-learning app providers can possibly incorporate aspects of gamification to enhance the user's enjoyable experience when using the apps. With respect to the extrinsic motivational factors, the present study showed that perceived usefulness had the highest influence on behavioral intentions. As such, it is important for m-learning app providers to educate potential users about the usefulness of their apps. For example, clearly communicating the learning goals which the app can help users to achieve might play a vital role in influencing their decision to accept and use the app. Also, peer networks can be used to promote m-learning apps, given that the social influence of significant others might push individuals to adopt and use m-learning apps.

Lastly, given that perceived usefulness is vital in shaping user decision to adopt m-learning apps, it is imperative to take into account the social cognitive aspects that influence perceived usefulness. For example, outcome expectancy has a significant direct influence on perceived usefulness, while self-efficacy has a significant indirect influence on perceived usefulness through the role of outcome expectancy. As such, it is imperative for m-learning app providers to actively promote the benefits of their systems and demonstrate use cases of how users are likely to reap rewards from using the apps. Also, they should ensure that the learning curve is low as users will be more likely to expect rewards from systems that they believe their skills are adequate to use (Lu et al., 2015; Rana & Dwivedi, 2015).

6.2. Limitations of the Study

This study has two main limitations that also provide the impetus for future studies. Firstly, entrepreneurial self-efficacy was measured using the four-item scale by Zhoa et al. (2005). There are several scales for measuring entrepreneurial self-efficacy. As such, even though Zhoa et al. (2005) demonstrated the validity of their scale relative to other entrepreneurial self-efficacy scales, the findings of this study might not necessarily be replicated for different measures of entrepreneurial self-efficacy. Secondly, the sample focused on small business owners; however, entrepreneurship m-learning apps can also be useful by potential entrepreneurs, entrepreneurship students, and nascent entrepreneurs. This thus limits the generalizability of the findings to all possible users of entrepreneurship m-learning apps.

7. CONCLUSION

An understanding of potential users' perceptions regarding a given technology is important in enhancing the acceptance and use of the technology. The purpose of the present study was to examine patterns that can unearth new insights in order to understand the determinants of m-learning app adoption. As such, the study presented a model for understanding user acceptance of m-learning apps using the social cognitive and motivational theories. The study focused specifically on entrepreneurship m-learning apps which provided the opportunity to further evaluate how the use of these apps enhances the entrepreneurial self-efficacy of the users, thus clearly showing the potential gains from using entrepreneurship m-learning apps. The proposed model explained 61.9% variance in behavioral intentions and 40.8% variance in use behavior. Additionally, the use of entrepreneurship m-learning apps was significant and positively associated with entrepreneurial self-efficacy. The findings of this study contribute to the growing literature on m-learning acceptance by demonstrating how novel constructs can be introduced into m-learning acceptance models to not only understand the mechanisms through which different factors influence its adoption but also the positive consequences of using the apps.

The efforts of this study can be expanded in the future by considering the following three points. Firstly, future studies can focus on addressing the limitations of this study. For example, the studies can use other measures of entrepreneurial self-efficacy to provide a more rigorous external validity of the proposed model. Likewise, future studies can test the model in different settings and with different groups of potential adopters of entrepreneurship m-learning apps in an attempt to improve the generalizability of the findings. Secondly, the proposed model in this study can be expanded with other relevant factors that have been shown to influence m-learning acceptance. For example, researchers can evaluate whether extending the model with a factor like perceived ease of use could provide a stronger explanatory power of behavioral intentions since ease of use is known to play a significant role in m-learning adoption (e.g. Poong et al., 2017). Thirdly, individual differences and demographic factors can be considered in future studies as this could provide an understanding of not only the acceptance of m-learning but also the positive benefits from using the m-learning apps.

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Information Resources Management Journal
Volume 32 • Issue 4 • October-December 2019

Understanding User Social Commerce Usage Intention:
A Stimulus-Organism-Response Perspective

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ABSTRACT

The integration of social media and e-commerce leads to the emergence of social commerce. Although previous research has examined social commerce user behaviour from multiple perspectives, it has focused on the effect of instrumental beliefs, such as perceived value, and has seldom examined the effect of emotional factors, such as sense of community on user behaviour. The purpose of this research is to draw on the stimulus-organism-response (SOR) model to examine the effect of sense of community on users' social commerce usage intention. The results indicate that both social support and service quality (stimulus) affect the sense of community (organism), which in turn affects users' sharing and participation intention (response). The results imply that service providers need to develop the user's sense of community in order to facilitate his or her social commerce usage intention.

KEYWORDS

Sense of Community, Social Commerce, SOR, Usage Intention

INTRODUCTION

E-commerce has been developing rapidly in the world. A report indicated that about 533 million Chinese users have conducted online purchase, accounting for 69.1% of its internet population (CNNIC, 2018). In the US, this figure is about 80% (Pew Research Center, 2016). At the same time, social media sites such as Facebook, Twitter and WeChat have been integrated with e-commerce, which leads to the emergence of social commerce, such as F-commerce (Facebook). In China, Jingdong (JD), a leading e-commerce company, has cooperated with Tencent, which is the largest social networking company. Users can access JD to conduct purchase via WeChat, a leading social networking platform developed by Tencent. These examples indicate that social commerce has been attached importance by enterprises. In the social commerce context, users interact between each other and exchange their opinions, ideas and experiences. This plays a great influence on users' behavioural decision. They rely on the comments, reviews and suggestions shared by other members rather than the information posted by online vendors to make their purchase decisions (Chen, Lu and Wang, 2017). However, prior research has found that users lack intention to participate in social commerce (Zhang, Lu, Gupta and Zhao, 2014) and share contents (Liang, Ho, Li and Turban, 2011; Chen and Shen, 2015). This

DOI: 10.4018/IRMJ.2019100104

may hinder the development of social commerce. A report indicated that 72% of online shoppers have never shared their purchase experiences (CNNIC, 2017). Service providers need to understand the factors affecting users' social commerce usage intention. Then they can adopt effective measures to facilitate user behaviour and ensure the success of social commerce.

The purpose of this research is to draw on the stimulus-organism-response (SOR) model to uncover the effect of sense of community on users' social commerce usage intention. The stimulus includes social support and community quality, which reflect the effect of community members and platforms, respectively. As users frequently interact between each other in social commerce communities, they may exchange social support, which reflects the advice, suggestions, empathy and encouragement. Social support including both informational and emotional support has been found to be a significant determinant of social commerce usage intention (Shanmugam, Sun, Amidi, Khani and Khani, 2016; Li and Ku, 2018). In addition, this research adopted three factors of system quality, information quality and service quality from the information systems (IS) success model to examine their effects on user intention (DeLone and McLean, 2004). These three factors reflect the community platform quality. The organism is represented by sense of community, which reflects a user's feelings of membership, belongingness and attachment to a community (Koh, Kim and Kim, 2003). Response includes sharing intention and participation intention, both of which have been examined as the social commerce users' behavioural variables (Zhang et al., 2014; Ko, 2018). We believe that SOR provides a useful lens to understand social commerce users' behavioral decision process, in which external stimulus affects the internal state that leads to user intention.

Previous research has examined users' social commerce usage intention from multiple perspectives, such as trust (Lu, Zeng and Fan, 2016a; Lu, Fan and Zhou, 2016b; Hajli, Sims, Zadeh and Richard, 2017), social interaction (Xiang, Zheng, Lee and Zhao, 2016; Zhang, Benyoucef and Zhao, 2016; Wang and Yu, 2017), and perceived value (Hu, Huang, Zhong, Davison and Zhao, 2016; Sun, Wei, Fan, Lu and Gupta, 2016; Chung, Song and Lee, 2017). However, it has mainly focused on the effect of instrumental beliefs such as perceived value and has seldom examined the effect of emotional beliefs on user behaviour. This may undermine our understanding of users' social commerce usage intention. Extant research has reported that an individual user's emotion is a significant determinant of his or her behaviour (Tsai and Bagozzi, 2014; Wan, Lu, Wang and Zhao, 2017). In this research, we examine users' social commerce usage intention from the emotional perspective of sense of community. When users interact with each other in a social commerce community, they may develop sense of community, which in turn affects their behavioural decision such as sharing and participation intention.

RESEARCH MODEL AND HYPOTHESES

Social Commerce Usage Intention

As an emerging model, social commerce usage intention has received great attention from information systems researchers. Due to the significant uncertainty and risk associated with social commerce, trust has been identified to be a significant factor affecting user behaviour. Kim and Park (2013) found that transaction safety, reputation and information quality affect users' trust in social commerce. Chen and Shen (2015) noted that social support affects trust, which in turn determines users' social sharing and shopping intention. Lu et al. (2016a) reported that institution-based trust affects users' transaction intention in social commerce marketplaces. Lu et al. (2016b) stated that social presence affects trust and a user's purchase intention in social commerce. These studies suggest that social commerce trust is affected by multiple factors such as reputation, social presence and social support.

In addition to trust, social interaction has also been examined in the social commerce context. As users conduct frequent social interaction, they may form close social networking relationships, which influence their behaviour. Wang and Yu (2017) argued that social interaction, which includes word-of-mouth (WOM) communication and observing other users' purchase, affects users' intention to purchase. Xiang et al. (2016) noted that parasocial interaction leads to users' impulse buying behaviour on social commerce platforms. Liu, Chu, Huang and Chen (2016) found that interpersonal interaction contributes to the flow experience, which reflects an optimal experience in social commerce. Zhang et al. (2016) stated that interactivity affects relationship quality, which in turn determines users' brand loyalty in social commerce. From these results, we can find that social interaction is a significant determinant of users' social commerce usage intention.

Previous research has also explored the effect of social support on user behaviour in the social commerce context. Liang et al. (2011) reported that social support including informational support and emotional support affects relationship quality and users' social commerce behaviour. Bai, Yao and Dou (2015) found that social support helps mitigate both product uncertainty and seller uncertainty, which in turn lead to social commerce users' purchase behaviour. Sun et al. (2016) stated that social support as a factor of social climate affects perceived value and users' purchase intention. These results highlight the necessity to take social support into consideration when examining social commerce user behaviour.

As evidenced by these studies, social commerce usage intention has been examined from multiple perspectives such as trust, social support and social interaction. However, they have seldom examined the effect of emotional beliefs such as sense of community on user intention. This research tries to fill the gap by drawing on the SOR model as the theoretical base.

SOR

The SOR originates from environmental psychology and it has been used to explain the effect of environmental factors on an individual user's psychological state and behaviour (Mehrabian and Russell, 1974). The theory proposes that environmental stimulus (S) may affect a user's internal state (O), which in turn affects his or her behavioral response (R). To some extent, stimulus reflects an input, whereas response reflects an output. Organism reflects the internal process. In this research, we include both social support and community quality as the stimulus (Hu et al., 2016), which reflect the effect of community members and platforms, respectively. The organism is represented by sense of community (Zhang, 2010), which reflects a user's affective states such as membership, belongingness and attachment to a community. Response includes both sharing intention and participation intention (Zhang et al., 2014). Sharing intention reflects a user's intention to share his or her experiences, advice and recommendations with other members (Chen and Shen, 2015), whereas participation intention reflects a user's intention to visit and use a community (Xu and Li, 2015).

SOR has been widely adopted to examine user behaviour in information systems research. Li, Dong and Chen (2012) examined the effects of both utilitarian and hedonic factors on mobile consumption experience. Zhang, Lu, Wang and Wu (2015) noted that site characteristics affect customers' co-creation experience and their intention to participate in co-creation. Hu et al. (2016) suggested that website features and peers' qualities affect shopping value, which further affects users' purchase intention. Liu et al. (2016) adopted SOR to find that interpersonal interaction affects the flow experience, which in turn affects purchase intention. These studies indicate that SOR provides a useful lens to explain user behaviour. This research generalizes it to the social commerce context.

Social Support

Social support reflects an individual user's experiences of being cared for, being responded to and being helped by other members in a community (Liang et al., 2011). As noted earlier, social support has been identified to be a significant factor determining user behaviour in social commerce (Zhang and Benyoucef, 2016). In line with these studies, we measured social support with two factors: informational support and emotional support (Liang et al., 2011). Informational support reflects the recommendations, advice, and suggestions that help to solve the problems (Liang et al., 2011). When users receive valuable information from other members, they may feel the utility and develop a sense of community, which includes membership and belongingness. Otherwise, they may feel that the community is useless to their working and life, which may lead to their disappointment and low sense of community. In addition, informational support can alleviate uncertainty and increase users' trust (Chen and Shen, 2015), which may help improve sense of community. Liang et al. (2011) found that informational support leads to a user's better relationship quality with a community. Lin (2011) reported that instrumental support (similar to informational support) affects a user's network ties and commitment to an instant messaging community. Thus, we suggest:

H1: Informational support is positively related to sense of community.

Emotional support reflects the caring, empathy and encouragement expressed by other members to an individual user (Liang et al., 2011). Compared to informational support that represents a direct support, emotional support is an indirect support. When users are in negative moods such as frustration and depression, they expect to receive emotional support from other members. The emotional support such as caring and encouragement may help relieve users' moods and facilitate their belongingness and attachment to a community. Lin, Hsu, Cheng and Chiu (2015) found that emotional support as a nurturant support affects community identification. Chen and Shen (2015) noted that emotional support affects a user's commitment to a community. Based on these results, we propose:

H2: Emotional support is positively related to sense of community.

Community Quality

In social commerce communities, users not only interact with other members, but also interact with the community platform. Thus, community platform quality as the stimulus may also affect their internal state. We draw on three factors of system quality, information quality and service quality from the IS success model to reflect the effect of community quality (DeLone and McLean, 2004).

System quality reflects the access speed, navigation and visual appeal of a community (Kim, Xu and Koh, 2004). System quality may form a user's initial impressions toward a community. When a community has fast access speed, effective navigation and an attractive interface, users may have good evaluations toward it and develop sense of community. In contrast, if the community has low system quality such as slow speed and a poor interface, users may feel that service providers lack the ability and integrity to provide quality platforms to them. They cannot develop belongingness and attachment to the community. Lin, Fan and Chau (2014) also found that system quality affects a user's sense of belonging to social networking sites. Thus, we suggest:

H3: System quality is positively related to sense of community.

Information quality reflects the relevance, timeliness and sufficiency of the information offered by communities (Kim et al., 2004). As information overload has become a common issue, providing relevant information to users based on their preferences is critical to ensuring a good experience (Hsu, Chang, Kuo and Cheng, 2017). This may help build users' trust in service providers and develop their identification to the community (Zhang et al., 2016). Similarly, timely and sufficient information may also demonstrate a service provider's trustworthiness. In contrast, users cannot build a sense of belonging to a community that provides low quality information to them. Thus, we suggest:

H4: Information quality is positively related to sense of community.

Service quality reflects the reliability, promptness and personalization of the services offered to a user (Kim et al., 2004). Users may expect to obtain reliable and personalized services when accessing social commerce communities. When this expectation is confirmed, they may become satisfied and develop a strong sense of community. In contrast, poor service quality may undermine a user's trust and his or her sense of belongingness and attachment. For example, if users wait much longer for the responses from communities, they may lack patience and drop their usage. Liang et al. (2011) found that service quality as a factor of website quality affects relationship quality, which includes trust, satisfaction and commitment. Thus, we state:

H5: Service quality is positively related to sense of community.

Sense of Community

Sense of community reflects an individual's feelings of relationship to a community (Koh et al., 2003). It often includes four factors: membership, influence, needs fulfillment and emotional connection (McMillan and Chavis, 1986). Membership reflects the feeling of belonging to a community. Influence reflects a user's feelings of control and influence over the community (Zhang, 2010). Needs fulfillment reflects that users believe that a community will meet their needs. Emotional connection reflects the bonds developed among community members. Prior research has found that sense of community significantly affects social networking user behaviour (Zhang, 2010; Oh, Ozkaya and LaRose, 2014; Mamonov, Koufaris and Benbunan-Fich, 2016). We propose that it may also affect users' social commerce usage intention.

When users develop a sense of community, they may be motivated to actively share contents and participate in a community. They are proud of being a member of the community and perceive their value and influence in the community. In addition, they feel a sense of belongingness and attachment to the community. These feelings including membership, influence, needs fulfillment and emotional connection may facilitate their sharing and participation in the community. Mamonov et al. (2016) reported that sense of community affects users' contribution in social networking sites. Xu and Li (2015) noted that sense of belonging to a community affects community participation. Consistent with these studies, we suggest:

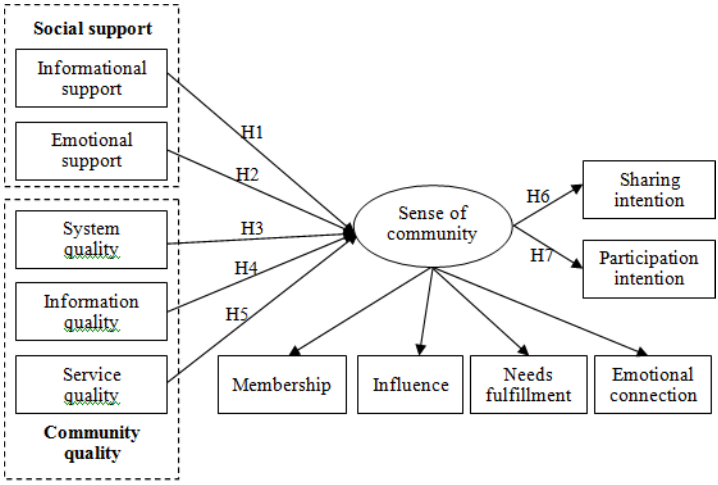
H6: Sense of community is positively related to sharing intention.
H7: Sense of community is positively related to participation intention.

Figure 1 presents the research model. Sense of community is a second-order factor, which includes four reflective factors: membership, influence, needs fulfillment and emotional connection.

METHOD

The research model includes eleven factors. Each factor was measured with multiple items. All items were adapted from extant literature to improve the content validity. Items of informational support and emotional support were adapted from Liang et al. (2011). Items of informational support (INS) reflect the advice and suggestions received from other members. Items of emotional support (EMS) reflect the caring, encouragement and empathy expressed by other members. Items of membership, influence, needs fulfillment and emotional connection were adapted from Zhang (2010). Items of membership (MEM) reflect the sense of belonging to a community. Items of influence (INFL) reflect a user's feeling of value and influence in a community. Items of needs fulfillment (NED) reflect that a community can meet a user's needs. Items of emotional connection (EMC) reflect the emotional bonds developed between members. Items of system quality, information quality and service quality were adapted from Zhou (2013). Items of system quality (SYS) measure the access speed,

Figure 1. Research model



navigation and visual appeal of a community platform. Items of information quality (INF) measure the timeliness, accuracy, sufficiency and relevancy. Items of service quality (SER) measure the reliability, personalization and promptness. Items of sharing intention (SHA) were adapted from Chen and Shen (2015) to reflect a user's intention to share his or her experiences and recommendations with other members. Items of participation intention (PAR) were adapted from Zhang (2010) to reflect a user's intention to participate in a community.

These items were first translated into Chinese by a researcher. Then another researcher translated them back into English to ensure consistency. When the instrument was developed, it was tested among twenty users that had social commerce experience. Then according to their comments, we revised a few items to improve the clarity and understandability. The final items and sources are listed in the Appendix.

Data were collected at a university campus. We believe that university students are an appropriate sample for this research because social commerce as an emerging business model is popular among young adults. The CNNIC report (2018) indicated that users that were between twenty and twenty-nine years old are the largest group (30%) of internet users. In addition, students represent a majority (25.4%) of internet users. These data suggest that university students are an important group of internet users. Previous research has also adopted university students as the sample (Sim, Tan, Wong, Ooi and Hew, 2014; Teo, Tan, Ooi, Hew and Yew, 2015; Wong, Tan, Tan and Ooi, 2015). Data were collected in September 2017 at an eastern China city, where e-commerce is more developed than other regions. We randomly contacted students in the university and inquired whether they had social commerce experience. Then we asked those with positive answers to fill the paper questionnaire based on their experience. We scrutinized all responses and dropped those with too many missing values. As a result, we obtained 339 valid responses. Among them, 59% of male and 41% were female. A majority of them (75.5%) were between twenty and twenty-nine years old. About one third (37.8%) of them have used social commerce communities for more than a year. The frequently used social commerce communities include WeChat, Sina Weibo, Dianping, and Meilishuo, which represent a few well-known communities.

We conducted two tests to examine common method variance. First, we performed a Harman's single-factor test (Podsakoff, MacKenzie, Lee and Podsakoff, 2003). The results indicated that the largest variance explained by an individual factor is 22.65%. Thus, none of the factors can explain the majority of the variance. Second, we modeled all items as the indicators of a factor representing the method effect, and re-estimated the model (Malhotra, Kim and Patil, 2006). The results indicated a poor fitness. For example, the goodness of fit index (GFI) is 0.473 (< 0.90). The root mean square error of approximation (RMSEA) is 0.173 (> 0.08). The results of both tests indicated that common method variance is not a significant problem in this research.

RESULTS

Following a two-step approach, we first examined the measurement model to test reliability and validity. Then we examined the structural model to test research hypotheses.

First, we conducted a confirmatory factor analysis to examine the validity, which includes convergent validity and discriminant validity. Convergent validity measures whether items can effectively reflect their factor, whereas discriminant validity measures whether two factors are statistically different. Table 1 lists the standardized item loadings, the average variance extracted (AVE), the composite reliability (CR) and Cronbach Alpha values. As listed in the table, most item loadings are larger than 0.7. Each AVE exceeds 0.5, and each CR exceeds 0.7. This indicated the good convergent validity (Gefen, Straub and Boudreau, 2000). In addition, all Alpha values are larger than 0.7, demonstrating good reliability.

To examine the discriminant validity, we compared the square root of AVE and factor correlation coefficients. As listed in Table 2, for each factor, the square root of AVE is significantly larger than its correlation coefficients with other factors, suggesting good discriminant validity (Gefen et al., 2000).

Second, we adopted structural equation modeling software LISREL to estimate the structural model. Figure 2 presents the results. Except H3 and H4, other hypotheses were supported. Four factors including membership, influence, needs fulfillment and emotional connection have high loadings on the second-order factor. Table 3 lists the recommended and actual values of a few indices. Except GFI, other fit indices have better actual values than the recommended values. The explained variance of sense of community, sharing intention and participation intention is 66.7%, 50.6%, and 7.5%, respectively.

DISCUSSION

As shown in Figure 2, informational support, emotional support and service quality significantly affect sense of community, which in turn affects both sharing intention and participation intention. We did not find the effect of system quality and information quality on sense of community.

Compared to informational support, emotional support has a larger effect ($\gamma = 0.61$, $P < 0.001$) on sense of community. This suggests that users are much concerned with the emotional support when developing sense of community. To some extent, informational support is instrumental, whereas emotional support is affective. Users not only expect to obtain useful information from other members, but also expect to obtain emotional comfort to relieve their moods. When users receive the caring and encouragement from other members, they may build identification with a community (Lin et al., 2015) and form a strong sense of community. Mamonov et al. (2016) has found that social interaction is a significant factor affecting sense of community in the context of social networking sites. Our results indicated that social support also affects sense of community. Thus, service providers need to encourage users' exchange of social support including informational and emotional support in order to enhance their sense of community.

Among three factors of community quality, only service quality has a significant effect ($\gamma = 0.14$, $P < 0.05$) on sense of community. This indicated that users attach great importance to the services received from communities. Quality services such as personalized and reliable services may help build users' trust (Liang et al., 2011) and enhance their sense of community. For example, service providers have adopted location-based services to offer the personalized information and

Table 1. Standardized item loadings, AVE, CR and alpha values

Factor	Item	Standardized Loading	AVE	CR	Alpha
Informational support (INS)	INS1	0.708	0.55	0.79	0.78
	INS2	0.829			
	INS3	0.686			
Emotional support (EMS)	EMS1	0.720	0.59	0.85	0.85
	EMS2	0.813			
	EMS3	0.813			
	EMS4	0.722			
Membership (MEM)	MEM1	0.728	0.53	0.77	0.76
	MEM2	0.822			
	MEM3	0.629			
Influence (INFL)	INFL1	0.785	0.53	0.81	0.81
	INFL2	0.776			
	INFL3	0.706			
	INFL4	0.621			
Needs fulfillment (NED)	NED1	0.807	0.65	0.84	0.84
	NED2	0.718			
	NED3	0.878			
Emotional connection (EMC)	EMC1	0.781	0.55	0.78	0.78
	EMC2	0.715			
	EMC3	0.720			
System quality (SYS)	SYS1	0.735	0.58	0.85	0.84
	SYS2	0.838			
	SYS3	0.771			
	SYS4	0.697			
Information quality (INF)	INF1	0.769	0.61	0.86	0.86
	INF2	0.795			
	INF3	0.804			
	INF4	0.756			
Service quality (SER)	SER1	0.775	0.61	0.83	0.83
	SER2	0.797			
	SER3	0.779			
Sharing intention (SHA)	SHA1	0.826	0.57	0.80	0.79
	SHA2	0.791			
	SHA3	0.637			
Participation intention (PAR)	USE1	0.653	0.51	0.76	0.76
	USE2	0.768			
	USE3	0.723			

Table 2. The square root of AVE (shown as bold at diagonal) and factor correlation coefficients

	INS	EMS	MEM	INFL	NED	EMC	SYS	INF	SER	SHA	PAR
INS	**0.744**										
EMS	0.504	**0.768**									
MEM	0.402	0.422	**0.731**								
INFL	0.558	0.566	0.555	**0.725**							
NED	0.469	0.424	0.455	0.359	**0.804**						
EMC	0.472	0.507	0.560	0.467	0.550	**0.739**					
SYS	0.003	0.010	0.041	0.064	0.006	0.033	**0.762**				
INF	0.111	0.064	0.108	0.079	0.111	0.060	0.539	**0.781**			
SER	0.114	0.115	0.063	0.038	0.191	0.193	0.447	0.574	**0.784**		
SHA	0.495	0.539	0.508	0.414	0.426	0.416	0.035	0.022	0.080	**0.756**	
PAR	0.109	0.202	0.189	0.088	0.152	0.310	0.179	0.140	0.144	0.114	**0.716**

Figure 2. The results estimated by LISREL

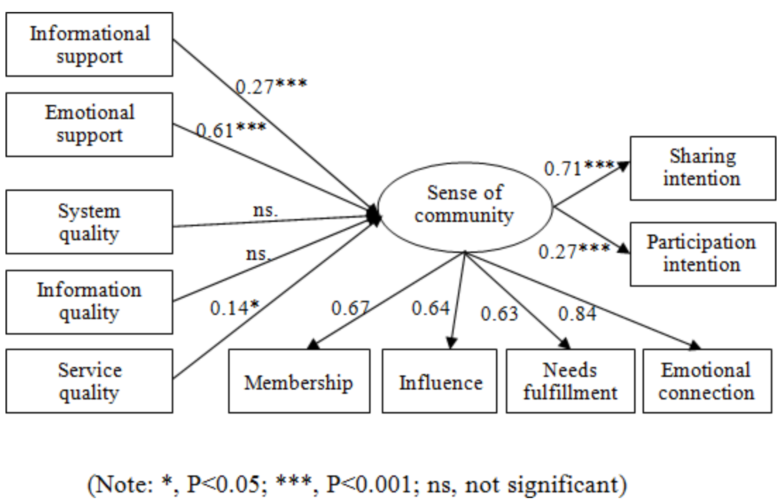


Table 3. The recommended and actual values of fit indices

Fit Indices	*chi²/df*	GFI	AGFI	CFI	NFI	NNFI	RMSEA
Recommended value	<3	>0.90	>0.80	>0.90	>0.90	>0.90	<0.08
Actual value	1.96	0.879	0.852	0.965	0.934	0.961	0.053

(Note: *chi²/df* is the ratio between Chi-square and degrees of freedom, GFI is Goodness of Fit Index, AGFI is the Adjusted Goodness of Fit Index, CFI is the Comparative Fit Index, NFI is the Normed Fit Index, NNFI is the Non-Normed Fit Index, RMSEA is Root Mean Square Error of Approximation) services to users based on their locations and preferences. This may help improve their sense of belongingness and attachment.

The results indicated that both system quality and information quality have no effect on sense of community. This is inconsistent with Zhang (2010), which found the effect of information quality on social networking users' sense of community in the US. The result may be explained for two reasons. First, our sample is composed of young adult users. They have relatively high self-efficacy and rich experience of using internet (Ifinedo, 2017). They are not much concerned with system quality when visiting a social commerce community. Second, our results found that informational support has a significant effect on sense of community. This suggests that users paid more attention to the information received from other members rather than that from the community. They may feel that compared to the information offered by a community, the information offered other members is more helpful and useful to their working and life (Wang and Yu, 2017).

Sense of community has four high-loading factors: membership, influence, needs fulfillment and emotional connection. This suggests that it is appropriate to measure sense of community as a second-order factor. This is consistent with prior research (Zhang, 2010). Among these four factors, emotional connection has a relatively larger loading (0.84) on sense of community. This highlights the central role of emotional connection in sense of community. The results indicated that sense of community affects both sharing intention and participation intention. The effect of sense of community on sharing intention is especially strong ($\beta = 0.71$, $P < 0.001$). These results show that sense of community is a significant factor determining users' social commerce usage intention.

IMPLICATIONS AND LIMITATIONS

From a theoretical perspective, this research draws on the SOR model to examine the effect of sense of community on users' social commerce usage intention. As noted earlier, although previous research has examined social commerce user behaviour from multiple perspectives such as trust, social interaction and perceived value, it has focused on the instrumental beliefs and has seldom disclosed the effect of emotional beliefs such as sense of community on user behaviour. This research tries to fill the gap. The results indicated that both social support and service quality as the stimulus affect sense of community, which in turn determines users' sharing and participation intention in social commerce. These results advance our understanding of social commerce user behaviour. Future research may pay more attention to the effect of emotional beliefs such as flow when examining social commerce user behaviour. Second, we found that social support, which includes informational support and emotional support, has a significant effect on sense of community. The effect of emotional support on sense of community is especially strong. This suggests that sense of community as an emotional belief receives significant influence from emotional support. These results extend extant research, which has found the effect of social interaction on sense of community (Mamonov et al., 2016). Third, the results indicated that service quality of a community significantly affects sense of community. Thus, offering reliable and personalized services is helpful for improving sense of community. This enriches extant research, which has reported the effect of information quality on sense of community in the social networking context (Zhang, 2010).

From a managerial perspective, the results imply that service providers need to develop users' sense of community in order to facilitate their social commerce usage intention. On one hand, service providers need to create a supportive climate in social commerce communities. They can use incentives such as points to encourage users' exchanging social support between each other. They can also encourage opinion leaders to actively offer social support and act as examples. On the other hand, they need to improve the community platform and offer quality services to users. They may use location-based services to offer contextual information to users. This may better meet users' needs and help develop their sense of community. At the same time, service providers need to be concerned with information privacy and should obtain users' permissions before pushing location-based services to them.

This research has the following limitations. First, the sample is mainly composed of university students. Although they represent an important group of internet users, future research needs to generalize the results to other samples, such as enterprise employees. Second, we focused on the effect of sense of community on user behaviour and neglected the possible effect of other control variables such as user experience and satisfaction. Future research can examine their effects. Third, we examined users' sharing and participation intention in this research. Although behavioral intention is a significant determinant of actual behaviour, future research needs to test the actual user behaviour. Fourth, we conducted a cross-sectional study. However, user behaviour is dynamic. Thus, a longitudinal research may provide more insights into user behavioural development.

ACKNOWLEDGMENT

This work was supported by National Natural Science Foundation of China (71771069), and NSFC-Zhejiang Joint Fund for the Integration of Industrialization and Informatization (U1509220).

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APPENDIX: MEASUREMENT SCALE AND ITEMS

Informational support (INS): Adapted from Liang et al. (2011):

- **INS1:** When I encountered a problem, some people in the community would give me information to help me overcome the problem.
- **INS2:** When faced with difficulties, some people in the community would help me discover the cause and provide me with suggestions.
- **INS3:** In the community, some people would offer suggestions when I needed help.

Emotional support (EMS): Adapted from Liang et al. (2011):

- **EMS1:** When faced with difficulties, some people in the community are on my side with me.
- **EMS2:** When faced with difficulties, some people in the community comforted and encouraged me.
- **EMS3:** When faced with difficulties, some people in the community listened to me talk about my private feelings.
- **EMS4:** When faced with difficulties, some people in the community expressed interest and concern in my well-being.

Membership (MEM): Adapted from Zhang (2010):

- **MEM1:** I feel that I am a member of the community.
- **MEM2:** I have been in the community for a long time.
- **MEM3:** I feel a sense of belonging to the community.

Influence (INFL): Adapted from Zhang (2010):

- **INFL1:** I have a chance to provide advice or suggestions to other members of the community.
- **INFL2:** Often there are some people that respond to my comments or the problems I posted in the community.
- **INFL3:** I am an active member of the community.
- **INFL4:** I care about what other members think of me.

Needs fulfillment (NED): Adapted from Zhang (2010):

- **NED1:** In the community, my needs can be satisfied.
- **NED2:** In the community, I can exchange with other members about the problems and get help.
- **NED3:** It is worthwhile to spend time on the community.

Emotional connection (EMC): Adapted from Zhang (2010):

- **EMC1:** I often discuss with other member of the community and enjoy the time.
- **EMC2:** In the community, I and other members witnessed a few important matters.
- **EMC3:** I have positive expectations toward the future of the community.

System quality (SYS): Adapted from Zhou (2013):

- **SYS1:** The community runs smoothly.
- **SYS2:** The community is easy to navigate.
- **SYS3:** The community is visually attractive.
- **SYS4:** The community quickly loads all the text and graphics.

Information quality (INF): Adapted from Zhou (2013):

- **INF1:** The community provides me with up-to-date information.
- **INF2:** The community provides me with accurate information.
- **INF3:** The community provides me with information relevant to my needs.
- **INF4:** The community provides me with sufficient information.

Service quality (SER): Adapted from Zhou (2013):

- **SER1:** The community provides reliable services.
- **SER2:** The community provides personalized services.
- **SER3:** The community provides prompt responses.

Sharing intention (SHA): Adapted from Chen and Shen (2015):

- **SHA1:** I am willing to provide my experiences and suggestions when other members of the community want my advice on something.
- **SHA2:** I am willing to share my own experience with other members of the community.
- **SHA3:** I am willing to recommend this community to other people.

Participation intention (PAR): Adapted from Zhang (2010):

- **PAR1:** If some people recommend this community to me, I will use it.
- **PAR2:** I am willing to spend more time and effort on participating in the community.
- **PAR3:** When I visit this kind of communities, this one is my first choice.

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Information Resources Management Journal

Volume 32 • Issue 4 • October-December 2019 • ISSN: 1040-1628 • eISSN: 1533-7979

An official publication of the Information Resources Management Association

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EDITORIAL

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