ABSTRACT

Because of the growing competition and challenges within the global business environment, understanding performance management has become essential to small and medium-sized enterprises (SMEs) as they have traditionally dominated the Chinese economy. In recognition of the limited studies with a specific focus on Chinese family SMEs, this study modelled and tested performance management by analysing four factors and eighteen indicators using structural equation modelling (SEM) and back-propagation neural network (BPNN). Secondary data from the Chinese Stock Market and Accounting Research (CSMAR) database were collected for this study. The results provide a better understanding of the proposed relationships between these variables through a review of their impact and correlations. This study suggested that four factors, including financial performance, external environment, internal environment, and enterprise development potential, will significantly impact performance management.

KEYWORDS
Chinese SME, Neural Network, Performance Management, Structural Equation Modelling

INTRODUCTION

In recent decades, Chinese SMEs developed rapidly to become the backbone of the Chinese economy (Jessica et al., 2021). They have played a significant role in fostering China’s rapid economic growth and are responsible for advancing the national employment and innovation. However, with the acceleration of globalization, Chinese SMEs face much greater competition in the global markets. In this ever-challenging environment, how performance should be evaluated has become a major concern, as this may have a long-term impact on the competitiveness and efficiency of a firm’s operations. Although performance management is considered a vital component as it has a critical impact on establishing and implementing strategic objectives within enterprises, studies have noted the lack
of performance measures that directly apply to the SME context (Garengo et al., 2005; Bahri et al., 2010). Studies focusing on performance management in Chinese family SMEs are especially scarce. Most SMEs in China are family-owned and managed enterprises, which historically have inherent organisational advantages because of their business structure (Chen & Hsu, 2009). However, due to changes within the business environment, their structural limitations have become more apparent, especially in relation to enterprise management issues caused by the difficulty in adjusting their existing framework (Chen et al., 2013). Notably, even when the scale of a family enterprise expands, its management model often remains concentrated at an entrepreneurial stage (Fang et al., 2021). In China, the success of family SMEs has received much attention due to their importance to the economy (Yang et al., 2020). However, previous studies have noted that the rate of failure among China’s family SMEs is quite high, with 68% failing within their first five years of operations, 19% surviving up to around 6–10 years, and only 13% of these firms have a lifespan that exceeds ten years (Zhu et al., 2012). This study attempts to understand performance management in Chinese family SMEs by testing a sample of firms listed in the Chinese Stock Market & Accounting Research (CSMAR) database using structural equation modelling (SEM) and back-propagation neural network (BPNN).

LITERATURE REVIEW AND MODEL DEVELOPMENT

Performance Management Tools

Today, organizations worldwide implement a range of performance management tools. These include popular methods such as Key Performance Indicators (KPI), 360-degree feedback Evaluation, Balanced Score Cards (BSC), as well as Management by Objectives (MBO). KPI is a method of performance management that ensures the achievement of corporate strategic objectives by extracting the key factors of an enterprise’s success and transmitting them to grass-roots units based on goal management (Tairova et al., 2021). BSC evaluates performance by utilizing both financial and non-financial indicators. Unlike traditional methods that focus solely on financial indicator analysis, BSC establishes a system that integrates internal processes, customers, learning, and development while incorporating finance as a component (Darestani & Nillofar, 2019). MBO is conducted accordingly: First, the enterprise puts forward specific business objectives to be realised in the future according to the actual operational situation. Next, employees of all departments and ranks would determine their personal goals based on the business objectives of the enterprise and their current situation. Finally, practical actions are taken by employees to realize their personal goals so that the enterprise can achieve its overall goals (Zhou & Xiong, 2020). 360-degree feedback evaluation focuses on the objectives of performance behaviours in an enterprise reviewed against the feedback assessment of stakeholders such as customers, the management, and employees (Priya & Renjitha, 2019).

Although widely used, these above methods have a common disadvantage, that is, they are adapted and replicated from Western firms that are structurally different from family SMEs in China. Implementing these methods requires rich experience and systematic theoretical knowledge, while results are only linked to task-oriented objectives and salaries. They do not align directly with employees’ promotion and career development, and therefore, they may limit effective management.

Factors Influencing Information Management of Performance in SMEs

Recognising the complexity within enterprises, studies have noted the limitations of relying only on traditional financial indicators in performance management and have highlighted the importance of including non-financial factors such as customers, products and markets, internal governance, and the development potential of an enterprise (Muhammad et al., 2021; Thapa et al., 2020; Wu et al., 2022). For the SEM analysis, the methodological approach taken by Wickramesekera and Oczkowski (2004) was followed, then BPNN analysis was undertaken using a sample of 195 Chinese family SMEs.
Financial Performance of an Enterprise

All business enterprises focus on achieving profitability; thus, including financial-related indices in performance indicators is a fundamental requirement (Omneya et al., 2021; Sun et al., 2020; Gian et al., 2019). However, other relevant indices that are derived through the evaluation of an enterprise’s internal and external environment and the realization of its crucial success should also be evaluated. If an enterprise’s overall performance improves, yet it cannot significantly improve its financial performance, it implies that the managers should reconsider their strategies and implementation plans. Based on this understanding, we propose the following hypotheses:

H1: An enterprise’s growth ability will positively affect performance management (O’sullivan & Abela, 2007).
   H1a: Profitability will positively affect performance management (Beard & Dess, 1981).
   H1b: Solvency will positively affect performance management (Taffler, 1983).
   H1c: Cash flow will positively affect performance management (Afrifa & Tingbani, 2018).
   H1d: Asset management will positively affect performance management (Wang & Wang, 2012).
   H1e: Asset quality status will positively affect performance management (Said, 2018).

External Environment of an Enterprise

An enterprise’s customers are essential to its long-term success and sustainability in its markets. Customers are concerned with quality, time, service, and cost when purchasing and using an enterprise’s products (Hirons et al., 1998; Rolstadås, 1998). Therefore, an enterprise needs to clarify its goals in terms of quality, time, service, and cost in the appraisal process and translate them into specific measurement indicators (Dragić, 2014; Hanggraeni et al., 2019). Based on these considerations, the following hypotheses are proposed:

H2: Customer satisfaction will positively affect performance management (Blessing & Natter, 2019).
   H2a: Market situation will positively affect the performance management (Erdem, 2020).
   H2b: Enterprise product control will positively affect performance management (Estrin & Rosevear, 1999).

Internal Governance of an Enterprise

An enterprise’s internal governance guides its procedures, decisions, and behaviours within its operations. Therefore, performance evaluation of internal activities should consider factors that may affect operational issues such as cycle time, quality, employee skills, and productivity (Huang et al., 2015). In addition, managers should cultivate continuous improvement in corporate governance as part of the enterprise’s core capabilities, foster project management procedures, and enhance safety standards (Ehler, 2003; Eldenburg et al., 2004; Schultz et al., 2010). Thus, the following hypotheses are proposed:

H3: Internal satisfaction of an enterprise will positively affect performance management (Vu & Nwachukwu, 2021).
   H3a: The internal governance structure will positively affect performance management (Teece, 1985).
   H3b: Management rules on stakeholder engagement will positively affect performance management (Ciemleja & Lace, 2011).
   H3c: Corporate governance structure will positively affect performance management (Said, 2018).
Development Potential

An enterprise’s potential for development impacts its sustainability and success, and as such, emphasis should be placed on its long-term operations, future investment, employee quality improvement, risk management, and technological innovation and learning ability (Eeha, 2015; Wang et al., 2020). Specific objectives should be put in place to enhance staff quality, establish a good information system, and improve abilities to encourage learning and growth. The following hypotheses are proposed:

H4: Industry development status will positively affect performance management (Ofori, 2000).
H4a: An enterprise’s core technology and innovation ability will positively affect performance management (Leung & Sharma, 2021).
H4b: Risk factors will positively affect performance management (Jia & Bradbury, 2021).
H4c: Quality of staff will positively affect performance management (Leung & Sharma, 2021).
H4d: Market growth potential will positively affect performance management (Rialp-Criado & Rialp-Criado, 2018).

METHODS

Structural Equation Modelling (SEM)

SEM is a widely-used statistical modelling technique for testing and analysing complex multivariate research data (Thomas & Hayes, 2021; Yu et al., 2021; Liu et al., 2021). SEM methodology incorporates a measurement model that examines the relationship between latent variables and their measures and a structural model that allows the testing of hypothetical dependencies in a model (Hoyle, 1995).

The Measurement Model

In SEM, the measurement model examines the relationship between latent variables and their measures, and their specific form is shown in equations (1) and (2) below (Sanita et al., 2021):

\[ x = \Lambda_x \xi + \delta \]  
\[ y = \Lambda_y \xi + \varepsilon \]

In the equation, \( x \) is a vector that includes exogenous indexes, \( y \) is a vector that includes endogenous indexes, \( \Lambda_x \) highlights the relationship between exogenous indexes and exogenous latent variables, that is, the factor load matrix of exogenous indexes on exogenous latent variables, \( \Lambda_y \) indicates the relationship between the endogenous indexes and the endogenous latent variable, that is, the factor loading matrix of the endogenous index on the endogenous latent variable, \( \delta \), and \( \varepsilon \) are error terms in the equations.

The Structural Model

The structural model allows the testing of relationships between latent variables, and its specific form is shown in equation (3) below (Shipley & Douma, 2021):

\[ \eta = B\eta + \Gamma\xi + \zeta \]
In the equation, \( h \) denotes the endogenous latent variables, \( \xi \) represents the exogenous latent variables, \( B \) refers to the relationship between the endogenous latent variables, \( \Gamma \) indicates the influence of the exogenous latent variables on the endogenous latent variables, and \( \zeta \) indicates the residual term that accounts for the unexplained part of \( \eta \) in the equation.

According to SEM rules, the above model needs to meet the following four conditions: First, there is no relationship between \( \varepsilon \) and \( \eta \); second, there is no relationship between \( \delta \); third, there is no relationship between \( \zeta \) and \( \xi \); and fourth, there is no relationship among \( \zeta \), \( \varepsilon \) and \( \delta \).

From these equations, coupled with the proposed models, each parameter can be calculated in the SEM through an iterative solution process.

Utilizing SEM as a research method has numerous advantages (Abe et al., 2021). First, it can consider measurement errors between independent and dependent variables to avoid bias in results. Next, the method allows simultaneous processing of multiple dependent variables and simultaneously estimating the structure and inter-factor relationships. Finally, SEM allows a more elastic measurement model, the ability to evaluate the complete model’s degree of fit, and the use of the path diagram can reveal the complex correlation between variables in the study.

**Back-Propagation Neural Network (BPNN) Model**

Many decades ago, the world was introduced to artificial neural networks (ANNs), which first originated in the middle of the 20th century. Today, ANN systems are recognised for their abilities in self-learning, information distribution and storage, and parallel processing. Hence, ANN tools have been frequently used in information processing and patterns recognition. ANNs have also performed well in intelligent modelling and intelligent control (Li et al., 2021). ANNs can be applied through a multi-layer perceptron using a back-propagation algorithm as an analytical tool. The BPNN form is a network composed of several layers of neurons, consisting of input layer nodes, output layer nodes, and one or more hidden layer nodes. It can approximate any continuous function with arbitrary precision. Hence, BPNN has a wide application in nonlinear modelling, function approximation, and pattern classification (Wang et al., 2021). A typical BPNN model with input, output, and hidden layers is shown in Figure 1.

**Figure 1. The structure model of BPNN**
Structurally, the three-layer BPNN includes an input layer, hidden layer, and output layer. No association is found between nodes at the same layer, and neurons at different layers propagate from forward to backward. The input layer contains several nodes, and the corresponding BP network can sense several inputs. The BP network will have several output data if the output layer contains several nodes. The node quantity in the hidden layer should be adjusted or set in response to the basis of the real situation. Having more hidden layer nodes will lead to higher accuracy in results, but this will also be a more time-consuming process. The specific function between each layer is shown in the following equations (Moldovanu et al., 2021):

The expression of the output function of nodes in the hidden layer reads:

$$b_r = f \left( \sum_{r=1}^{m} W_{ir} \cdot a_i + T_r \right) \quad (r = 1, 2, \ldots, u)$$

(4)

The expression of the output function of nodes in the output layer reads:

$$c_j = f \left( \sum_{r=1}^{n} V_{jr} \cdot b_r + \theta_j \right) \quad (j = 1, 2, \ldots, n)$$

(5)

The input layer node is $a_i$, and $W_{ir}$ indicates the connection weight to the hidden layer node $b_x$. $V_{jr}$ is the connection weight between the hidden layer node $b_x$ and the output layer node $c_j$. $T_r$ and $\theta_j$ are the threshold of the hidden layer node and output layer node, respectively. $f(\bullet)$ is the transfer function, and the S-type transfer function is usually selected. It is shown in equation (6) below:

$$P = \left(1 + e^{-x}\right)^{-1}$$

(6)

The maximum is close to 1, and the minimum is close to 0. Normally, 0.5 is selected as the threshold. In performance management research, the variable is completely correlated to 1, and the variable is not correlated to 0. If the $p$-value obtained by calculation is higher than 0.5, it indicates that the variable correlation degree is high; if the $p$-value is obtained smaller than 0.5, it indicates a low correlation between variables.

The specific learning process of BP network is as follow:

1. It is to randomly assign a smaller value to $W_{ir}$, $T_x$, $V_{jr}$, $\theta_j$.
2. The following operations should be conducted on each node ($A^{(k)}, A^{(k)}) (k = 1, 2, \ldots, p)$:

   ⊗ the value of $A^{(k)}$ should be input into the input layer node, which becomes the activation value $a_i$ of the input layer node. Then, it is essential to calculate forward in turn;

   ⊗ the error between the output node output $c_j$ of the output layer and the expected output value $c_j^{(k)}$ is calculated.

$$d_j = c_j - c_j^{(k)}$$

(7)
Reverse allocation of errors to hidden layer nodes:

\[ e_z = b_x * (1 - b_x) * \left( \sum_{j=1}^{n} V_{xj} * d_j \right) \]  

(8)

Adjust the connection weight \( W_{ir} \) between the input layer and the hidden layer node and the hidden layer node threshold \( T_r \):

\[ W_{ir} = W_{ir} + \beta * a_i * e_r \]  

(9)

\[ T_r = T_r + \beta * e_r \left( 0 < \beta < 1 \right) \]  

(10)

Step , is repeated until the error \( E_{AV} \) becomes small enough for \( j = 1, 2, \ldots, n, k = 1, 2, \ldots, p \)

\[ E_{AV} = \frac{1}{2} \sum_{k=1}^{p} \sum_{j=1}^{n} \left( c_j - \bar{c}_j \right)^2 \]  

(11)

\( E_{AV} \) is the target function of training. After multiple iterations training, the error \( E_{AV} \) meets the accuracy required in the specific problem.

The learning process of BPNN algorithm can be summarised into the following two phases (Huang et al., 2021).

1. Forward propagation of the working signal: the input signal is transmitted from the input layer to the output layer through the hidden unit, and the output signal is generated at the output end, which is the forward propagation of the working signal. During the forward transmission of the signal, the weight of the network is fixed. Besides, the state of neurons in each layer only influences the state of the neurons in the next layer. The error signal is transferred to the back-propagation if the desired output cannot be obtained in the output layer.

2. Back-propagation of error signal: the error signal is the difference between the actual output of the network and the expected output. It propagates forward layer by layer from the output end, which is the backward propagation of the error signal. In this process, the error feedback adjusts the network’s weight. Repeated correction of weights can make the network’s actual output closer to the expected output.

**Data Source and Sample**

This study used secondary data on Chinese family SMEs listed in the Chinese Stock Market and Accounting Research (CSMAR) database to screen data. The CSMAR database is valued as a reliable and reputable data source that consolidates a comprehensive collection of statistics on Chinese listed companies, and it has been extensively used by researchers studying Chinese businesses (Krause et al., 2019; Li et al., 2019). In China, listed family SMEs are concentrated on the Chinese SME Board, and these firms are required to disclose detailed and comprehensive operations information (Zhou et al.,
2015). Therefore, family firms listed in the SME Board were sampled for this research, consisting of 195 firms. This sample size adheres to the sample size requirement for using SEM (Hair et al., 2018).

**ESTABLISHMENT OF THE MODEL**

**Construction of the Structural Equation and Path Diagram**

As noted earlier, this study models performance management in Chinese family SMEs by focusing on four factors: financial performance, external environment, internal governance, and enterprise development potential. Drawing on established research, hypotheses are proposed based on the perceived relationships between the variables, and the model was tested (Don et al., 2020). We propose that the external operations of an enterprise is an exogenous latent variable, while financial performance, internal governance, and the development potential of the enterprise are endogenous latent variables. Furthermore, each endogenous latent variable is influenced by its corresponding observed variables.

Based on these proposed relationships, the path diagram of this study is detailed in Figure 2.

**Figure 2. The path diagram of the structural equation**

The definition of each parameter in the path diagram of the structural equation is as follows.

- y1 - customer satisfaction; y2 - market condition; y3 - enterprise product control; x1 - profitability; x2 - solvency; x3 - enterprise growth ability; x4 - cash flow; x5 - asset management indicators; x6 - asset quality status; x7 - internal satisfaction of enterprise; x8 - corporate internal governance structure; x9 - corporate external governance structure; x10 - corporate governance structure; x11 - industry development status; x12 - enterprise core technology and innovation ability; x13 - risk factors; x14 - quality of staff; x15 - market growth potential.
Incorporating the above-mentioned variables, the structural equation is shown in equation (12) below:

\[
\begin{pmatrix}
\eta_1 \\
\eta_2 \\
\eta_3
\end{pmatrix} = \begin{pmatrix}
\beta_{21} & 0 & \beta_{23} \\
0 & 0 & 0 \\
0 & 0 & 0
\end{pmatrix}
\begin{pmatrix}
\eta_1 \\
\eta_2 \\
\eta_3
\end{pmatrix} + \begin{pmatrix}
\gamma_{21} & \gamma_{22} & 0 \\
0 & 0 & \gamma_{33}
\end{pmatrix}
\begin{pmatrix}
\xi_1 \\
\xi_2 \\
\xi_3
\end{pmatrix} + \begin{pmatrix}
\zeta_1 \\
\zeta_2 \\
\zeta_3
\end{pmatrix}
\] (12)

The specific meaning of each parameter in the structural equation is as follow:
1: \(3\times1\) vector, endogenous latent variable; 2: \(3\times1\) vector, exogenous latent variable; 3: residual of the structural equation; 4: relationship coefficient between endogenous latent variables; 5: influence of exogenous latent variables on endogenous latent variables.

**BPNNS Structural Design**

The BPNNS structural design used the following five procedures.

1) Determination of the number of neurons in the input layer: The input layer receives input data, so the number of nodes in the input layer of the BPNNS model is the number of input variables, which depends on the number of indicators. After filtering through SEM, the number of nodes in the input layer of the BPNNS is determined.

2) Determination of the number of neurons in the output layer: The selection of output nodes corresponds to the evaluation results, so it is necessary first to determine the expected output (Yang et al., 2020). The expected output of the research object is the overall evaluation of enterprise information management of performance appraisal, so the neuron quantity in the output layer is determined to be 1. The set of evaluation is set to five levels: good, better, common, worse, and worst. The highest and lowest score are set. For example, 0 and 1 can be evaluated by the following principles: 1>output result<0.9, high correlation; 0.9>output result<0.7, higher correlation; 0.7>output result<0.5, common correlation; 0.5>output result<0.3, lower correlation; the output result is <0.3, low correlation.

3) Determination of the neuron quantity in the hidden layer: the neuron quantity in the hidden layer of the BPNNS is related to the neuron quantity in the input and output layers. In addition, it is related to factors such as the problem complexity, the conversion functional form, and the characteristics of the sample data. With too few neurons in the hidden layer, the network may either not reach specific accuracy or may not be properly trained. Although including more neurons can reduce system error, the network training process may be prolonged. Besides, the training may easily fall into a local minimum without achieving the best advantage. This risk is also the potential internal reason for the appearance of an over-fitting phenomenon. To avoid over-fitting during training and ensure sufficiently high network performance, the primary principle of determining the neuron quantity in the hidden layer is to make the structure as compact as possible while meeting the accuracy requirements (Li et al., 2020).

4) Setting training parameters: In the BPNNS model, setting the error to 0.0001 can enhance result accuracy. Generally, the BPNNS model can achieve satisfactory results with 500 iterations of training and learning (Wen et al., 2020).

5) Designing transfer function: The transfer function is very important to the effect of the BPNNS. In academia, sigmoid-type functions are generally used. The transfer function from the input to the hidden layer is the logsig-type transfer function, while the transfer function from the hidden layer to the output layer is the tansig function (Zhu et al., 2020; Wu, 2020).
RESULTS

Reliability Analysis and Fit Indices

For reliability analysis, statistical software SPSS was used to evaluate the internal consistency coefficient and to measure the reliability of the sample data. The model’s internal consistency coefficient $\alpha$ of the corresponding four research factors, including financial performance, internal environment, external environment, and enterprise development potential, were calculated, and the results are shown in Figure 3.

Figure 3 shows that the coefficient values are above 0.7; this is in line with accepted statistical guidelines requiring the value to exceed 0.7 (Hair et al., 2018). Therefore, it is appropriate for this study to apply these four predictor variables to predict a firm’s overall performance.

Next, the AMOS fit indices were reviewed to assess model fit. The Normed Chi-Square ($\chi^2$/df) is 3.211. The Goodness of Fit Index (GFI) is 0.932, Normed Fit Index (NFI) is 0.981, Comparative Fit Index (CFI) is 0.976, and the Root Mean Square Error of Approximation (RMSEA) is 0.021. These values are within the recommended guidelines between acceptable to good fit (Hair et al., 2018).

SEM ANALYSIS RESULTS

The proposed model was tested using the Analysis of Moment Structures (AMOS) software. AMOS is a commonly used software in SEM-based research studies and is a suitable tool for covariance structural analysis and analysis of complex multivariate data. Figure 4 presents the analysis results.
From this analysis, the relationship between the four latent variables can be explained: (1) The impact of financial performance on performance management is significantly positive, with an impact coefficient of 0.86. Financial performance plays a crucial impact in performance management; (2) The impact of the internal environment on financial management is positive. However, the impact coefficient is weak at 0.32, which suggests a small impact of the internal environment on performance management; (3) The impact of the developmental potential on performance management is also positive but with limited impact based on the coefficient of 0.38, suggesting that the developmental potential has little impact on performance management; (4) The impact of the external environment on financial management is significantly positive. The impact coefficient is 0.69. On the other hand, the impact of the external environment on performance management is moderate, with an impact coefficient of 0.69. The results of the hypothetical validation analysis for the model’s eighteen indicators are detailed in Table 1.

Table 1. Validation analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standardization factor</th>
<th>Simulation result</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1 Profitability</td>
<td>9.46</td>
<td>9.42</td>
<td>+++</td>
</tr>
<tr>
<td>X2 Solvency</td>
<td>8.89</td>
<td>8.58</td>
<td>+++</td>
</tr>
<tr>
<td>X3 Corporate growth ability</td>
<td>7.89</td>
<td>7.29</td>
<td>++</td>
</tr>
<tr>
<td>X4 Cash flow</td>
<td>8.43</td>
<td>8.30</td>
<td>+++</td>
</tr>
</tbody>
</table>

Table 1 continued on next page
The number of “+” in the table indicates the degree of relevance.

Based on the validation analysis as shown in Table 1, the indicators enterprise internal governance structure (X8), corporate external governance structure (X9), corporate governance structure (X10), risk factors (X13) have the worst correlation to performance management. To further understand the importance of the correlative indicators, 14 indicators of ‘++’ and ‘+++’ were selected as input items for the BPNN simulation.

**BPNN SIMULATION RESULTS**

After 14 nodes were determined in the input layer, the range of the nodes quantity in the hidden layer of the BPNN was set to 5-20. Using MATLAB software, it was required to program first before inputting the sample data. After learning and training, the failure rate and training time were calculated. Next, the number of nodes in the hidden layer was adjusted, with the last determined at 11. Training times and results are shown in Figure 5:
After 500 iterations of learning and training with the sample data using the Trainrp function, the result met the requirement of the error target of 0.0001 (Figure 5). The final result was obtained after the specific output result was compared with the expected value, as shown in Figure 6.

Figure 5. Results of learning and training

After 500 iterations of learning and training with the sample data using the Trainrp function, the result met the requirement of the error target of 0.0001 (Figure 5). The final result was obtained after the specific output result was compared with the expected value, as shown in Figure 6.

Figure 6. Output results
From the above simulation analysis, seven of the fourteen indicators have the greatest impact on performance management in China’s family SMEs: profitability, solvency, cash flow, enterprise core technology, and innovation capabilities, quality of staff, customer satisfaction, and market conditions. The other seven indicators have a low-to-moderate impact on performance management in China family SMEs: enterprise growth ability, asset management indicators, asset quality status, internal satisfaction of the enterprise, industry development status, market growth potential, and enterprise product control. The BPNN simulation supports the SEM analysis with similar results and provides an effective and confirming robustness check on the analysis.

CONTRIBUTIONS, LIMITATIONS, AND CONCLUSION

This research addresses the current gap in studies that emphasize Chinese family SMEs. Using SEM and BPNN, performance management in Chinese family SMEs was analysed by testing four factors and eighteen related indicators. The generated results provide a better understanding of the proposed and hypothesized relationships between the variables in this study, highlighting the importance of profitability, solvency, cash flow, enterprise core technology and innovation ability, quality of staff, customer satisfaction, and market conditions on performance management. Thus, this study enriches the SME performance literature. Furthermore, as a practical contribution, this study has the potential to provide suggestions to listed Chinese family SMEs regarding which kinds of performance indicators can be emphasized to improve a performance management. For example, the results show that financial performance plays a key role in the performance management process.

The limitations of this study should be noted. First, the focus on China’s SMEs may restrict this study as the findings may not be generalisable to foreign firms outside China and non-SMEs. Next, in this exploratory study, we had a limited sample size (N=195), preventing a test and retest of the proposed model. This was partly overcome by using BPNN, but a test and retest should be conducted in future studies. Also, this research analyzed only secondary data obtained through the CSMAR database; only indicators with recorded information on the database were considered. Subsequent follow-up studies should use a range of primary data to analyze the variables and their proposed relationships.
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Kaiyang Sun’s study is about Chinese family SMEs’ governance and innovative management.

Alvin Tan is an accomplished lecturer in International Business at QUT. He specializes in the internationalization of firms and has a research interest SME export management.

Ying Xian Wang’s research interests are mainly on Chinese modal semantics, i.e. modal particles and modal adverbs, which constitute a difficult area for learners of Chinese as a foreign language.

Rumintha Wickramasekera is an Associate Professor in International Business at the Queensland University of Technology (QUT) Business School, Brisbane, Australia. His research is focused on identifying the sustainable internationalization process of small to medium sized enterprises (SMEs), including his PhD research, which examined the internationalization of the Australian wine industry.


