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# Effect of Social Media and Data Analysis Technology on Employee Work Motivation

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**Abstract:** There is limited research on the relationship between social media and employee motivation, specifically in the context of knowledge examination. Therefore, this study introduces data analysis technology to explore the relationship between social media and employee motivation, and proposes corresponding hypotheses. Meanwhile, experiments are used to validate the algorithm and hypotheses. The experiment indicates that as the minimum support increases, the actual running time decreases rapidly. Currently, with a minimum support of 0.5, the running time has decreased from over 1000 seconds to approximately 50 seconds. In the mean error comparison, the algorithm's value is below 0.015%, much lower than that of the comparison algorithm, while in the acceleration ratio comparison, its value is always above 0.9, much higher than that of the comparison algorithm. In the field investigation and analysis, the actual variance result of Model 1 has an F-value of 2.55. Model 2 and Model 3 add explanatory power to this foundation, while Models 4 to 7 yield the same results. In addition, the 95% confidence interval for the bootstrap mediation effect for both the direct and indirect effects of social media with two orientations passes through zero. The use of social media by employees in businesses significantly affects their work status, and certain content can boost their enthusiasm for work. Overall, the proposed algorithm effectively mines the relationship between social media and employee motivation, and all proposed hypotheses have been validated. Social media has a significant positive effect on employee motivation, which can be effectively applied in practical employee management within the enterprise.

**Keywords:** Social media; data analysis technology; performance; body; employee motivation.

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## 1. Introduction

The rapid development and widespread use of Social Media (SME) are profoundly affecting the knowledge ecosystem within enterprises, as well as the communication, sharing, interaction, and collaboration between employees (Farivar and Richardson, 2021). SME tools are gradually entering the workplace, and companies are strategically using them to help employees carry out their work and improve their business behavior (Labban and Bizzi, 2022). In enterprises, different types of SME platforms can coexist and be compatible, and employees can use these platforms for external communication and internal collaboration (Susanto et al., 2023). The rapid development of SME platforms has attracted close attention from society and academia, and most scholars have confirmed their positive impact on work. It plays an important role in motivating employees, including internal communication tools (such as Slack and Microsoft Teams) that focus on team collaboration and process management, facilitating the flow of information between employees in real time. Social networks (such as Facebook and LinkedIn) provide a space for employees to showcase their career achievements and build connections, thereby enhancing a sense of belonging through shared success stories. Professional forums, such as GitHub, encourage the sharing of expertise and technical exchange, and motivate employees to innovate. However, due to differences in SME dimensionality, there is still debate about its effectiveness and its ability to motivate employees (Sukumar et al., 2021). The rapid development of SME platforms has attracted widespread attention from society and academia. Most scholars have verified the positive effects of SME use on work, but due to the different dimensions of SME division, there is still controversy over its effectiveness. SME, as a set of web applications that aggregate technological and social functions, enables people to discover, share, store, and integrate new knowledge from multiple information channels on the internet. Therefore, SME provides an environment where employees can connect and benefit from valuable knowledge exchange. However, existing research has always focused on how SME changes affect knowledge-related activities, but no study has examined the relationship between the use of SME for knowledge acquisition and employees innovation performance.

Meanwhile, current research rarely examines the relationship between knowledge-based SME usage and employee innovation performance, and rarely directly involves employee motivation. Therefore, this study analyzes the relationship between knowledge-based SME usage and employee motivation by introducing data analysis techniques and proposing corresponding hypothesis validation. Its purpose is to clarify the relationship and the effectiveness of the application between SME and employee motivation, and to provide a reference for enterprise management practices.

The study is separated into four aspects. The first section is a summary and discussion of current domestic and international research on the use of corporate SME or employee motivation. The second section is an analysis of SMEs and data analysis techniques that motivate employees, including the introduction of relevant algorithms and the formulation of corresponding hypotheses. The third section validates the algorithm and assumptions. The fourth section summarizes the entire article.

## 2. Literature Review

SME, as a new type of online media, enables individuals to create and share their own content through openness, connectivity, and other means. With the gradual development of information technology, SME has transitioned from a single network technology to a network platform model that integrates multiple information technologies and functions. The use of SME has not only been widely adopted by users in work and life but has also sparked a wave of research among many scholars in the academic community. Steinmetz et al. (2021) addressed reduced employee satisfaction stemming from blurred work-life boundaries and introduced a corporate SME to strengthen these boundaries, thereby improving employee satisfaction and motivation. Meske and Junglas (2021) conducted a corresponding survey on the frequency of SME use in enterprises in response to issues related to the digital transformation of enterprises, thereby supporting the construction of enterprises digital workplaces and helping to improve employees work enthusiasm. Liang et al. (2021) conducted a survey on the effectiveness of SMEs in practical enterprise applications and on employee satisfaction across different SME platforms to analyze the substantive relationship between the two and motivate employees. This provided data support for improving employee job satisfaction. Laitinen and Sivunen (2021) conducted an empirical analysis of the various constraints on employees use of corporate SME, which effectively reduced these constraints and helped increase the frequency of employees sharing information on corporate SME. Addressing how different types of workshop performance feedback affect employee motivation and engagement, Marodin et al. (2023) proposed a performance feedback analysis method based on socio-technical systems theory. Research results showed that production, improvement, and individual performance feedback had significant positive effects on relevant output, while safety and quality performance feedback had no statistically significant effects on motivation or engagement (Laitinen and Sivunen, 2021). Mutha and Srivastava (2023) proposed a method to enhance employee engagement under leadership influence, addressing limited social communication and a lack of information exchange in virtual teams. Research showed that leaders played an important role in enhancing virtual employee engagement, and that inter-team trust had a profound impact on employee engagement and mediated the effect of leadership communication on employee engagement. Therefore, this study provided practical value for organizations seeking to improve internal communication and team participation by guiding managers in adapting to the virtual work environment through suggestions on leadership styles and skills training.

In addition, Weber and Haseki (2021) collected relevant data from a large multinational company through case analysis to address issues related to the use of SME in actual enterprise e-commerce environments. This provided theoretical support for establishing good communication between sales personnel and customers. Chen et al. (2021) summarized existing theoretical models to construct a causal chain framework for the practical application of SME platforms in enterprises. This effectively explained the relationship between the use of comfortable SME and employee satisfaction, job performance, and job motivation. Agnihotri et al. (2022) studied the impact of SME on the digital supply chain environment using binary survey data and constructed a conceptual model to address the issue of SME churn in enterprise supply chains. This provided data supporting the advantages of SME use in enterprises and the promotion of employee motivation. Islam et al. (2021) conducted a detailed analysis of the regulatory capabilities of corporate SME in response to issues related to the use of SME in enterprises. This effectively reduced employees workload and fatigue.

The above studies indicate that current research rarely examines the relationship between knowledge-based SME usage and employee innovation performance, and few directly address employee motivation. Therefore, this study explores the relationship by introducing relevant data analysis techniques and proposes innovative methods in view of corresponding hypotheses.

## 3. SME and Data Analysis Technology for Employee Motivation

SMEs have been widely used in current enterprises, but there is still debate about their effectiveness and whether they motivate employees. Therefore, this section primarily uses data analysis techniques to examine the relationship between the two and to propose hypotheses.

### 3.1. Methodology

To analyze the relationship between knowledge-based SME usage and employee motivation, this study employs appropriate data analysis methods to clarify it. In response to practical problems, this study chooses the association rule algorithm of data mining technology to achieve the mining of the relationship between SME and employee motivation, and introduces the idea of ontology to improve association rule data mining (Masood et al., 2023; Sinha et al., 2022; Tianxing et al., 2021). The actual process of ontology-assisted association rule mining is shown in Fig. 1.

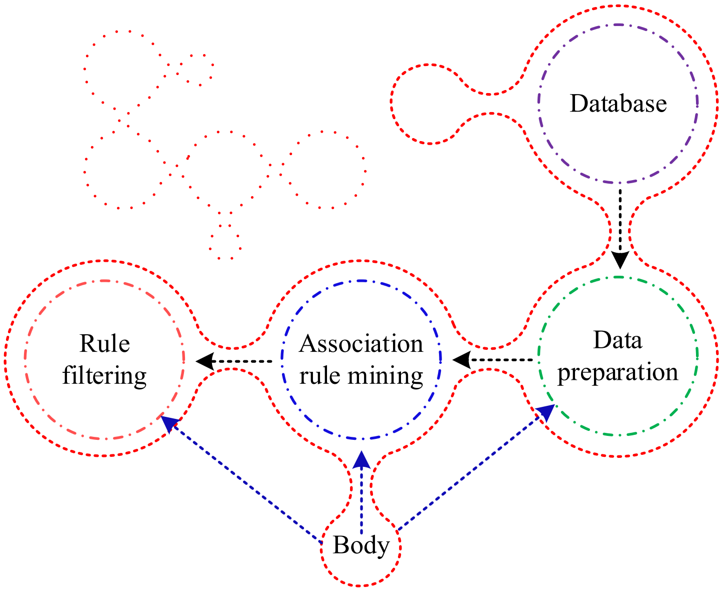



**Fig. 1.** Schematic diagram of the actual process of ontology assisted association rule mining

Fig. 1 clearly shows that ontology assisted association rule mining typically involves three aspects: preparation of relevant data, optimization of association rule mining algorithms, and rule filtering. Its advantage lies in its ability to use ontological methods to select suitable objects based on factors, such as the levels and dimensions involved, thereby yielding useful sets of association rules at each level (Abu-Salih et al., 2021). Secondly, the use of ontology methods reduces redundancy in generating frequent items (Hassan and Behadili, 2022). In addition, using an ontology can prune association rules that are not of interest, thereby enabling the discovery of new knowledge from the resulting set. In view of this, this study adopts a formula that combines ontology to calculate the minimum support at different levels. The calculation is given in Eq. (1).

$$L_{\min} = \min\left(L_1, \cdots, L_{\max\_lv}\right) \tag{1}$$

In Eq. (1), $L_{\min}$ represents the minimum number of items at the same level.

$$L_{\max} = \max\left(L_1, \cdots, L_{\max\_lv}\right) \tag{2}$$

In Eq. (2), $L_{\max}$ represents the maximum number of items at the same level.

$$\min\_\sup[l] = \max\_z - \frac{L_l - L_{\min}}{L_{\max} - L_{\min}} \times \left(\max\_z - \min\_z\right) \tag{3}$$

In Eq. (3), $\max\_z$ represents the maximum support level. $L_l$ represents the number of items in the $l$ layer. $\min\_z$ represents the minimum support level. Therefore, the Multi-layer Association Rules Mining Algorithm in View of Ontology (MARO-FP) optimizes both content and process, as shown in Fig. 2.

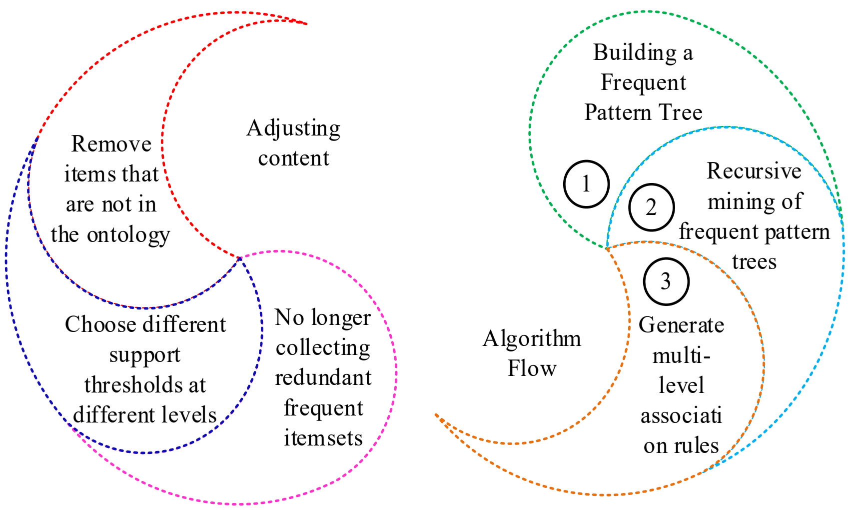



**Fig. 2.** MARO-FP algorithm optimization process and flowchart

Fig. 2 clearly shows that its optimization adjustment combines the transaction database and ontology, removing items not in the ontology for each transaction and expanding each transaction. Meanwhile, different support thresholds are selected at different levels, and redundant frequent itemsets are no longer collected when generating the corresponding frequent itemsets. The actual steps of the algorithm are as follows: first, construct a frequent pattern tree based on the ontology. Then, recursively mine the frequent pattern tree to generate multi-level frequent itemsets. Finally, it generates multi-level association rules based on multi-level frequent itemsets. However, not all strict rules can innovate employee performance and continuously motivate employees, so it is necessary to interpret the filtered multi-level association rules as valuable knowledge. Among them, redundant rules are defined in three ways. If rule $G$ is redundant, assuming that one item is the ancestor of another item, it is filtered. The expression of rule $G$ is shown in Eq. (4).

$$G : P_1 \wedge P_2 \cdots \wedge P_m \Rightarrow Q_1 \wedge Q_2 \cdots \wedge Q_n \tag{4}$$

In Eq. (4), $P_m$ and $Q_n$ represent the preceding and following terms of the rule. The second definition is that if rule $G$ is redundant, assuming that each term in rule $G'$ is a descendant of its corresponding internal term or the same term, and there is a confidence level for rule $G$, then $G$ is a descendant of $G'$. When the confidence level of $G$ varies with a given constant and falls within the expected confidence interval, $G$ is filtered. The expression of $G'$ is shown in Eq. (5).

$$G' : P_1' \wedge P_2' \cdots \wedge P_m' \Rightarrow Q_1' \wedge Q_2' \cdots \wedge Q_n' \tag{5}$$

In Eq. (5), $P_m'$ and $Q_n'$ are the preceding and following terms of rule $G'$. The confidence level expression of rule $G$ is shown in Eq. (6).

$$\gamma(G) \in \left[\exp\left(\gamma(G)\right) - \beta, \exp\left(\gamma(G)\right) + \beta\right] \tag{6}$$

In Eq. (6), $\gamma(G)$ represents the confidence level of rule $G$. $\beta$ represents the given constant. The expression of $\exp\left(\gamma(G)\right)$ is shown in Eq. (7).

$$\exp\left(\gamma(G)\right) = \left(\lambda(Q_1)/\lambda(Q_1')\right) \times \cdots \times \left(\lambda(Q_n)/\lambda(Q_n')\right) \times \gamma(G_1') \tag{7}$$

In Eq. (7), $\lambda(Q_n)$ represents the support of item $Q_n$. The third definition is that if rule $G''$ is redundant, it is assumed that rule $G'''$ exists and there is a confidence level for rule $G''$, and $G''$ is removed when there is no significant difference between the confidence level of $G''$ and the confidence level of $G'''$. Among them, the expressions of rules $G''$ and $G'''$ are shown in Eq. (8).

$$\begin{cases} G'' : X \wedge Z \Rightarrow Y \\ G''' : X \Rightarrow Y \end{cases} \tag{8}$$

In Eq. (8), $X$, $Z$, and $Y$ represent the set of items, while $Z$ is not an empty set. The confidence level expression of rule $G''$ is shown in Eq. (9).

$$\gamma(G'') \in \left[\gamma(G''') - \alpha, \gamma(G''') + \alpha\right] \tag{9}$$

In Eq. (9), $\alpha$ represents the given constant.

### 3.2. Hypotheses Development and Results

The MARO-FP algorithm is utilized to investigate the correlation among SME usage, employee knowledge acquisition, and motivation. In real enterprises, what directly drives employee motivation is the actual acquisition of funds by employees, which is also linked to employee innovation performance. Therefore, this study primarily analyzes the impact of SME use on employees innovation performance, which, in turn, affects employees innovation motivation. To deeply understand the mechanism by which SME usage affects employee motivation, this study introduces the Social Cognitive Theory and the Uses and Gratifications Theory as the core theoretical frameworks. The Uses and Gratifications Theory, from the audience's perspective, explains why individuals actively choose specific media to meet their needs. This theory holds that employees' use of SME is an active choice based on specific needs. When employees use SME for work purposes, they can more effectively obtain knowledge and resources directly related to their work, thereby enhancing their work performance and innovation. Therefore, the use of work-oriented SMEs positively impacts employee motivation. Similarly, social-oriented usage meets employees needs for social belonging and emotional support, helps reduce work stress, enhances organizational identification, and indirectly stimulates work enthusiasm. Therefore, it is recommended:

J1: Work-oriented SME usage has a significant positive impact on employee motivation.

J2: Social-oriented SME usage has a significant positive impact on employee motivation.

The Social Cognitive Theory emphasizes the triadic interaction among individual behavior, personal cognition, and environmental factors. This theory holds that an individual's behavior is influenced not only by the external environment but also by cognitive factors such as beliefs, expectations, and self-efficacy. In the enterprise context, SME, as an environmental factor, influences employees cognitive state through providing knowledge sharing, social support, and feedback mechanisms, thereby changing their work behavior and innovative performance. SME, as an information-rich environment, regardless of whether used for work-oriented or social-oriented purposes, can broaden employees knowledge channels and promote knowledge acquisition. Work-oriented usage directly brings professional knowledge and task information. Socially oriented use indirectly promotes knowledge acquisition through interpersonal interaction and observational learning. Therefore, it is proposed that the following:

J3: Work-oriented SME usage positively promotes employees knowledge acquisition.

J4: Social-oriented SME usage positively promotes employees knowledge acquisition.

According to the trinary interaction of determinism in the Social Cognitive Theory, personal cognition (knowledge acquisition) is the key mediating variable connecting the environment (SME usage) and behavior (innovative performance). The more knowledge employees gain through SME, the stronger their problem-solving abilities and innovative self-efficacy will be, making them more likely to exhibit innovative behaviors and innovative motivations. Therefore, it is recommended:

J5: Knowledge acquisition has a significant positive impact on employee motivation.

J6: Knowledge acquisition plays a mediating role between work-oriented SME usage and employee motivation.

J7: Knowledge acquisition plays a mediating role in social-oriented SME usage and employee motivation.

The above hypotheses collectively constitute the theoretical model of this study, as shown in Fig. 3.

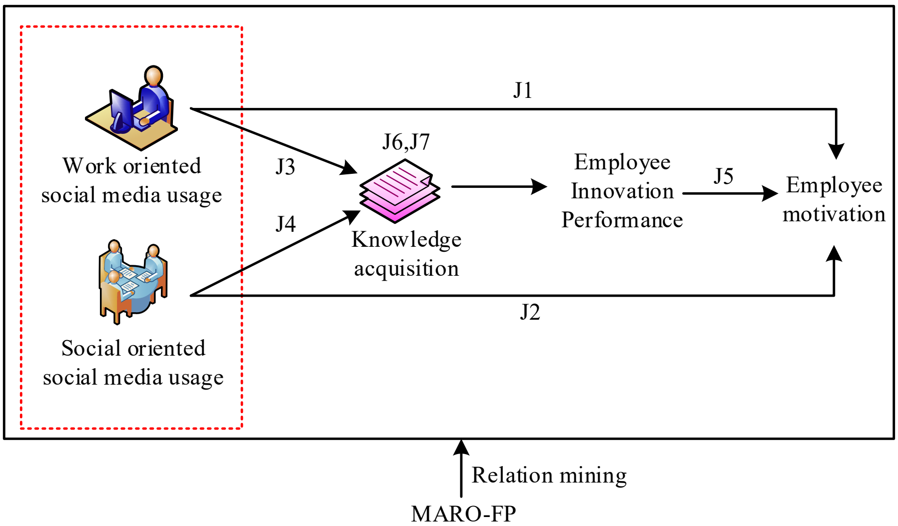



**Fig. 3.** Conceptual model proposed in view of hypothesis theory

Fig. 3 shows that the conceptual model is established strictly in view of seven research hypotheses, starting with SME and ultimately targeting employee motivation, thereby clearly demonstrating the application of SME to employee motivation. Meanwhile, in addition to analyzing the relationships among the three, the MARO-FP algorithm is used to mine them. In actual experiments, this study selects mature scales that have been empirically tested for measurement. The SME scale content is divided into four and five types based on work orientation and social orientation (all types assume the use of SME). There are four questions in the knowledge acquisition scale, each rated on a 5-point Likert scale. Employee innovation performance includes employees actively promoting innovative ideas, among other activities and comprises nine question types. To better clarify the overall design logic of this study, Fig. 4 presents the complete process from the data source to the final hypothesis verification.

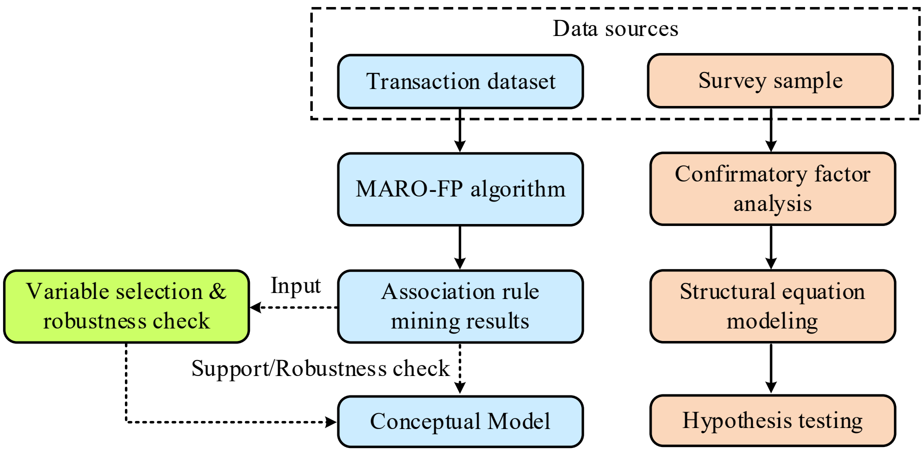



**Fig 4.** Logical diagram of the study design

As shown in Fig. 4, this study first uses the MARO-FP algorithm to mine association rules from the transaction data, aiming to identify significant co-occurrence relationships among SME usage, knowledge acquisition, and employee innovation performance, thereby providing a basis for the subsequent construction of the conceptual model and variable selection. Subsequently, using data collected through questionnaire surveys, Confirmatory Factor Analysis (CFA) and SEM are employed to statistically test the hypotheses in the conceptual model, thereby comprehensively revealing the mechanism by which SME influences employee motivation. The dotted arrows in the figure indicate that the MARO-FP algorithm's mining results provide information support for the conceptual model, while the solid arrows represent the data flow and analysis steps.

## 4. MARO-FP Algorithm Validation, SME Application Data Analysis, and Hypothesis Testing

### 4.1. Dataset Description and Preprocessing

This study used two datasets: the transaction dataset (to verify the performance of the MARO-FP algorithm) and the questionnaire survey dataset. The experimental environment was equipped with an Intel Core i7-10750H CPU operating at 2.60 GHz, 16GB of memory, and Windows 10. The transaction dataset was derived from the actual operational records of multiple enterprises in the Pearl River Delta region, covering industries such as technology, manufacturing, and services. It contained a total of 193,289 transaction records. Each record corresponded to an employee's SME usage behavior during a specific period, and the data pattern is shown in Table 1.

**Table 1.** Description of transaction dataset fields

| Field name | Type | Description | Example value |
|---|---|---|---|
| TransactionID | String | Transaction unique identifier | T20231001_001 |
| EmployeeID | String | Employee number | EMP12345 |
| Timestamp | Date and time | Time of behavior occurrence | 45200.39583 |
| Platform | String | Social media platform | "Work Group on WeChat" |
| ActionType | String | Type of behavior (such as posting, commenting, liking, sharing) | "Posting" |
| Content | Text | Content of the post/comment (de-sensitized) | "Project Progress Report" |
| ItemSet | List of strings | Key words/concept items extracted from the content (mapped to the ontology) | ["Work Report", "Project A"] |

Table 1 lists the field names, types, descriptions, and example values of the transaction dataset. The data preprocessing steps include the following: (1) Data cleaning: Remove transaction records with missing TransactionID or empty ItemSet (a total of 1,247 records were deleted, and 192,042 records remained). (2) Item generalization: Generalize specific keywords to predefined concept levels based on the ontology O (for example, "WeChat work group" is generalized to "Work-oriented SME"). (3) Transaction compression: Merge similar behaviors of the same employee within consecutive 1-hour periods to reduce redundancy. (4) Support calculation: Count the frequency of each item's occurrence to be used for subsequent association rule mining.

To verify the performance of the MARO-FP algorithm, this study selected two representative data mining algorithms as the baselines. Baseline algorithm A was the Enhanced Scalable Stacked Forest, which is based on the ensemble learning framework of random forests and improves the mining accuracy by stacking multiple hierarchical classifiers. This study was implemented using the scikit-learn library in Python 3.8 (version 1.0.2), with the following main parameter settings: the number of trees n_estimators=100, the maximum depth max_depth=10, the minimum sample split min_samples_split=5, and other parameters kept at their default values. Baseline algorithm B was the unsupervised anomaly mining for high-dimensional big data algorithm, which is based on the Isolation Forest principle and identifies abnormal patterns by randomly partitioning the feature space. This study was implemented using the PyOD Python library (version 1.0.7), with the main parameters: anomaly ratio contamination=0.1, number of trees n_estimators=100, and sampling size max_samples=256. Both baseline algorithms were run on the same transaction dataset, using the same support and confidence thresholds as MARO-FP (min_sup=0.05, min_conf=0.6). The evaluation indicators were Root Mean Square Error (RMSE), MAE, and speedup.

The questionnaire survey dataset was targeted at the employees of enterprises in the Pearl River Delta region that use SME. To enhance the representativeness of the sample, a stratified random sampling method was adopted, based on the industry (technology, manufacturing, services), enterprise size (<100 people, 100-500 people, >500 people), and employee position (entry-level employees, middle-level managers, senior managers). This ensured that each stratum had sufficient samples. The questionnaire used a five-point Likert scale (1=completely disagree, 5=completely agree), and the measured variables included: work-oriented SME usage (5 questions), socially oriented SME usage (4 questions), knowledge acquisition (4 questions), and employee innovation performance (9 questions). Control variables included gender, education level, years of work, and position.

Sampling frame: A sampling frame was constructed from the enterprise list provided by local industrial associations and chambers of commerce, covering major cities in the Pearl River Delta, including Guangzhou, Shenzhen, Zhuhai, and Foshan.

Approximately 1,200 employees contact details from enterprises were included. Within each enterprise, 1 to 5 employees meeting the inclusion criteria were randomly selected. Inclusion criteria: ① Currently employed and with a work history of ≥ 1 year. ② Using SME (either work-oriented or social-oriented) at least once a week in the past three months. ② Voluntarily participating and completing the questionnaire. Exclusion criteria: ① Questionnaire completion time less than 2 minutes. ② Answers showing obvious regularity (such as all selecting the same option). ③ A large number of missing values for key variables (more than 20%).

A total of 450 questionnaires were distributed, and 371 were retrieved, yielding an effective recovery rate of 82.4%. Z-score standardization was applied to continuous variables to control for dimensionality, and samples with short filling times or regular responses were removed. A total of 12 samples were removed, leaving 359 samples. The distribution of the valid samples is shown in Table 2, covering employees across different industries, enterprise sizes, and position levels, indicating that the sample is well-representative.

**Table 2.** Distribution of valid samples (N=371)

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Industry | Technology | 148 | 39.9 |
| | Manufacturing | 112 | 30.2 |
| | service | 111 | 29.9 |
| Enterprise size | < 100 people | 89 | 24 |
| | 100-500 people | 156 | 42 |
| | More than 500 people | 126 | 34 |
| Position | Entry-level employees | 198 | 53.4 |
| | Middle-level managers | 123 | 33.2 |
| | Senior managers | 50 | 13.5 |

Furthermore, to verify the direct impact of SME usage on employees work performance, this study collected additional SME behavior data (likes, comments, replies, forwards) and work status evaluations from 165 employees in an enterprise in the eastern region as supplementary samples for empirical analysis. This enterprise was in the technology industry, and employees used Enterprise WeChat for both internal and external communication. The data collection period was a continuous three months.

To test whether the current sample size was sufficient to detect the expected effect, the study conducted a post hoc sensitivity analysis using G*Power 3.1. For the main hypothesis test (multiple linear regression with 5 predictor variables), $\alpha$=0.05 was set, with statistical power (1-$\beta$)=0.80. It was calculated that the minimum detectable effect size (f2) was 0.035 when N=371. This corresponded to a moderately small effect size, indicating that the sample size was sufficient to detect the actual significant relationship. For the mediation effect test, the bias-corrected Bootstrap method was used. When the sample size reached 300 or more, a power of 80% could be achieved at a medium effect size. This study's N=371 met this requirement. For the supplementary sample N=165, with $\alpha$=0.05 and a power of 0.80, the minimum detectable effect size $f^2$ in simple linear regression was 0.048 (corresponding to an R2 of approximately 0.045), still allowing detection of a moderately small effect. Therefore, this sample size was reasonable for analyzing the relationship between SME behavior and work performance.

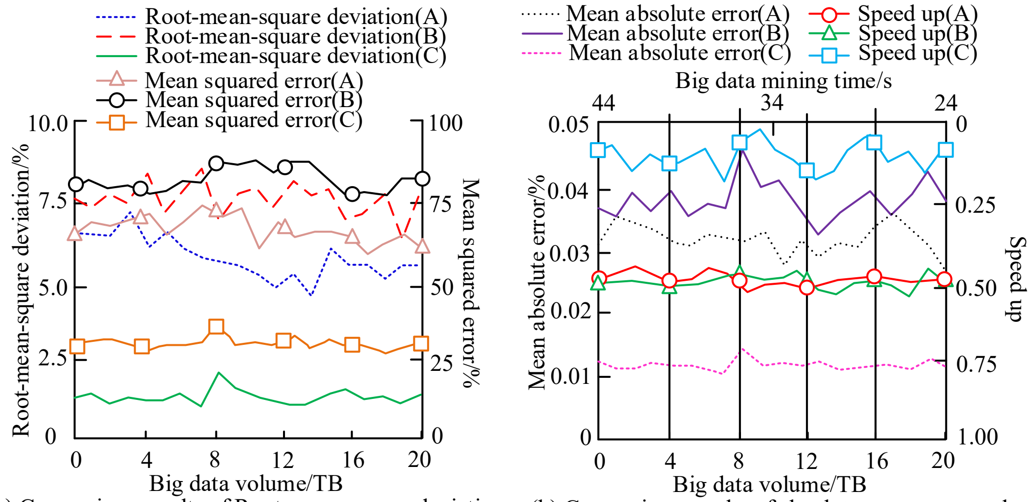
### 4.2. Verification of Algorithm Performance

To further verify the application effect of the MARO-FP algorithm, this study used Root-mean-square deviation (Fig. 5(a)), Mean absolute error, and acceleration ratio as evaluation indicators. For comparison, we introduced a big data mining algorithm based on an enhanced scalable stacked forest (Algorithm A) and an unsupervised anomaly mining algorithm for high-dimensional big data analysis (Algorithm B). The results are presented in Fig. 5.

In Fig. 5(a), the Root-mean-square deviation of the MARO-FP algorithm was far lower than that of the comparison algorithm, consistently remaining below 20%. The MAE was also lower than that of the comparison algorithms shown in Fig. 5(b), remaining at about 50%. In addition, in the MAE comparison, the MARO-FP algorithm achieved an MAE below 0.015%, and the acceleration ratio remained above 0.9 in the mid-term comparison shown in Fig. 5(b). Overall, the MARO-FP algorithm performed well and was effective for SME, knowledge acquisition, employee motivation, and association rule mining.

### 4.3. Data Analysis and Hypothesis Testing

Before conducting the hypothesis test, the measurement model's reliability was assessed to ensure the validity of the subsequent analysis. In this study, SPSS 22.0 and MPLUS 7.0 were used to conduct CFA and reliability and validity tests on the questionnaire survey data (N=371). The reliability test primarily assessed the scale's internal consistency. The Cronbach's $\alpha$ coefficients and Composite Reliability (CR) of each variable are shown in Table 3. The Cronbach's $\alpha$ coefficients of all variables were higher than the recommended threshold of 0.7, ranging from 0.81 to 0.89. The CR values of the combined reliability were all higher than the recommended threshold of 0.8, ranging from 0.82 to 0.90, indicating that the scale has good internal consistency reliability. Convergent validity was evaluated through Average Variance Extracted (AVE). As shown in Table 3, the AVE values for each variable were all above the recommended threshold of 0.5, ranging from 0.53 to 0.64. This result indicated that the measurement indicators effectively explained most of the variance in the corresponding latent variables and that convergent validity was good.




(a) Comparison results of Root-mean-square deviation and Mean squared error of three algorithms

(b) Comparison results of absolute error mean and acceleration ratio of three algorithms

**Fig. 5.** Comparison results of 3 algorithms and 4 indicators

**Table 3.** Results of reliability and convergence validity tests

| Variable | Number of items | Cronbach's α | CR | AVE |
|---|---|---|---|---|
| Work-oriented social media usage | 5 | 0.86 | 0.87 | 0.58 |
| Social-oriented social media usage | 4 | 0.83 | 0.84 | 0.57 |
| Knowledge acquisition | 4 | 0.81 | 0.82 | 0.53 |
| Employee innovation performance | 9 | 0.89 | 0.9 | 0.64 |

Discriminant validity was used to assess differences among constructs. This study employed two methods for the test: the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). According to the Fornell-Larcker criterion, the square root of the AVE of each variable should be greater than the correlation coefficient between that variable and other variables. As shown in Table 4, the square root of the AVE of each variable is greater than the correlation coefficient of the row and column to which it belongs, indicating good discriminant validity.

To evaluate the overall goodness of fit of the measurement model, this study conducted a CFA of the four-factor model (work orientation, social orientation, knowledge acquisition, and employee innovation performance). The model-fitting indices are shown in Table 5: $\chi^2$/df=2.98, GFI=0.93, Total Learning Index (TLI) =0.92, CFI =0.93, Root-Mean-Square Error of Approximation (RMSEA) Deviation =0.07, and Standardized Root Mean Squared Residual (SRMSR) =0.05. All indicators reached or exceeded the critical values, indicating a good fit between the measurement model and the data. In the subsequent multiple regression analysis and SEM, the reported path coefficients were standardized to eliminate the influence of different variable scales and facilitate comparison of each variable's relative contribution to the outcome variable. The standardized coefficients usually ranged from -1 to 1, and their significance was assessed using t-values or Bootstrap confidence intervals.

**Table 4.** Tests of discriminant validity (Fornell-Larcker criterion)

| Variable | Work orientation | Social orientation | Knowledge acquisition | Innovation performance |
|---|---|---|---|---|
| Work orientation | 0.76 | - | - | - |
| Social orientation | 0.64 | 0.75 | - | - |
| Knowledge acquisition | 0.42 | 0.43 | 0.73 | - |
| Innovation performance | 0.53 | 0.53 | 0.64 | 0.8 |

Note: The bolded diagonal values represent the square root of AVE. The lower triangle shows the correlation coefficients between variables (all $p$<0.01).

**Table 5.** Confirmatory factor analysis fitting index

| Indicators | $\chi^2$/df | GFI | TLI | CFI | RMSEA | SRMSR |
|---|---|---|---|---|---|---|
| Four-factor model | 2.98 | 0.93 | 0.92 | 0.93 | 0.07 | 0.05 |
| Critical value | <3.0 | >0.90 | >0.90 | >0.90 | <0.08 | <0.08 |

Therefore, to assess the performance of the MARO-FP algorithm, this study conducted a field investigation of the relationships among the three variables and performed correlation and hypothesis testing. Among them, in the correlation analysis, gender (D), education (E), working experience (M), and position (G) were set as control variables, and the four hypothetical variables of work-oriented SME usage, social-oriented SME usage, knowledge acquisition, and employee innovation performance were set as H, I, K, and L. The results are shown in Table 6.

**Table 6.** Correlation analysis results between control variables and hypothetical variables

| - | D | E | M | G | H | I | K | L |
|---|---|---|---|---|---|---|---|---|
| Mean value | 1.49 | 2.15 | 2.39 | 1.53 | 3.81 | 3.81 | 4.02 | 3.84 |
| Standard deviation | 0.50 | 0.62 | 1.17 | 0.,0 | 0.84 | 0.83 | 0.57 | 0.65 |
| D | 1.00 | 0.01 | -0.14** | -0.17** | 0.10 | 0.11** | 0.04 | -0.04 |
| E | - | 1.00 | -0.03 | 0.01 | 0.01 | 0.05 | 0.04 | 0.04 |
| M | - | - | 1.00 | 0.52** | -0.03 | 0.01 | 0.13* | 0.13** |
| G | - | - | - | 1.00 | 0.01 | 0.07 | 0.09 | 0.19** |
| H | - | - | - | - | 1.00 | 0.64** | 0.42** | 0.53** |
| I | - | - | - | - | - | 1.00 | 0.43** | 0.53** |
| K | - | - | - | - | - | - | 1.00 | 0.64** |
| L | - | - | - | - | - | - | - | 1.00 |

Note: * represents $p<0.05$, * * represents $p<0.01$.

Table 6 clearly shows that the average usage of work-oriented SME is 3.81, the average usage of social-oriented SME is 3.81, the average knowledge acquisition is 4.02, and the average innovation performance of employees is 3.84. In terms of variable correlations, there were significant positive correlations between work-oriented and social-oriented SME usage, knowledge acquisition, and employee innovation performance. That is, they were significantly positively correlated with employee motivation ($p<0.01$). This result supported the research hypothesis. Therefore, the study tested 8 hypotheses on this basis. Among them, seven models were constructed for hypothesis testing: Model 1 included the control variables D, E, and M. Model 2 added the hypothesis variable H to the three control variables. Model 3 incorporated the hypothesis variable I, building on Model 1. Model 4 incorporated the hypothesized variable K based on Model 1. Model 5 had the same variables as Model 1, Model 6 and Model 2 had the same variables, and Model 7 and Model 3 had the same variables. The difference was that the Variance Inflation Factor (VIF) for the variables entering the regression equation in models 1-3 ranged from 1.001 to 1.021, whereas in models 5-7, all VIFs were less than 2 (as shown in Fig. 7). Therefore, assuming the validation results of J1, J2, and J5 are shown in Fig 6.

Figs. 6(a) and (b) represent models 1 to 4. In view of the multiple regression statistics in Fig 6(b), in the actual variance result of Model 1, the F-value was 2.55, and the $p$-value was greater than 0.05, indicating that the actual explanatory ability of the model is significantly insufficient, and the linear relationship between the control variable and the dependent variable is not significant. Model 2 had an F-value of 39.99 and a $p$-value of less than 0.01 after adding the hypothesis variable H (Fig. 6(a)). Similarly, Model 3 has significantly increased its explanatory power relative to Model 2. Overall, the use of work-oriented and social-oriented SMEs had a significant positive impact on employees innovation performance, which in turn affected employees motivation. Hypotheses J1 and J2 have been validated, while the results of Model 4 show that knowledge acquisition also had a significant positive impact on employee innovation performance. Hypothesis 5 has been validated. The validation results of J3 and J4 are shown in Fig 7.

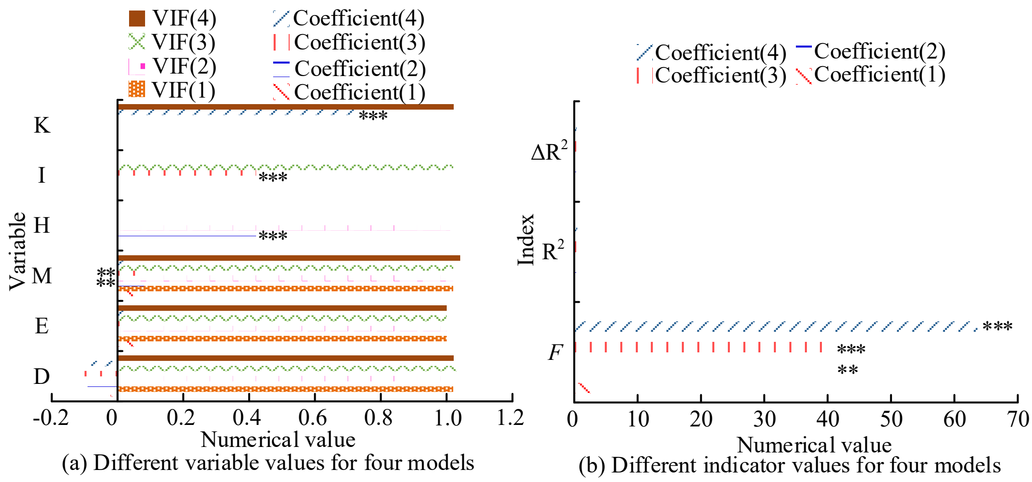



**Fig. 6.** The relationship between work and socially oriented SME usage and employee innovation performance
Note: ** indicates $p<0.01$*** Indicates $p<0.001$.

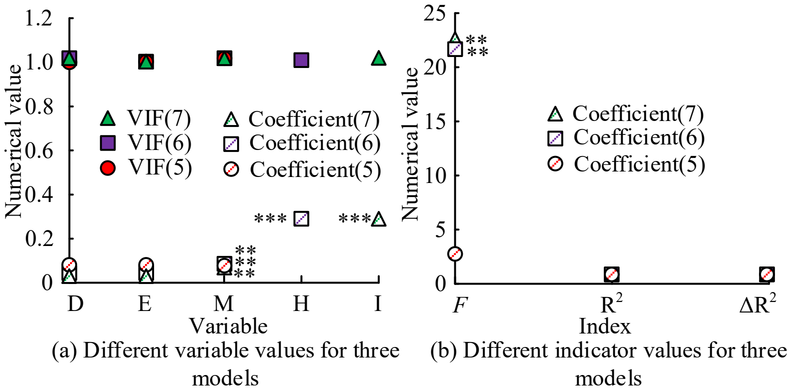



**Fig 7.** The impact of work and socially oriented SME usage on knowledge acquisition

In Fig 7(a), models 5 to 7 are represented. Fig. 7(b) demonstrates that the hierarchical regression results showed a significant impact of work-oriented and social-oriented media use on knowledge acquisition. The former was the experimental result for Model 5, with a coefficient of 0.28, a p-value < 0.001, and an R2 of 0.19. The latter were the experimental results of Model 6, with a coefficient of 0.29, a p-value < 0.001, and an R2 of 0.20. Overall, the results of hierarchical regression clearly supported hypotheses J3 and J4, that is, both work-oriented and social-oriented SME usage accelerated the actual communication efficiency and the way information existed and spread. It was beneficial for users to obtain more knowledge resources. Assuming that in the validation of J6 and J7, the use of work-oriented SME to employee innovation performance through knowledge acquisition was an indirect path 1, and without knowledge acquisition was a direct effect 1. The impact of socially oriented SMEs on employee innovation performance was mediated by path 2, indirectly through knowledge acquisition and by path 1, directly without knowledge acquisition. The results are shown in Table 7.

**Table 7.** Fit of mediation model, Mesomeric effect value and effect quantity results

| Intermediary model fit | | | | | | | |
|---|---|---|---|---|---|---|---|
| - | $\chi^2$ | $df$ | $\chi^2/df$ | GFI | TLI | RMSEA | SRMSR |
| H and I→K→L | 604.34 | 203.00 | 2.98 | 0.93 | 0.92 | 0.07 | 0.05 |

| Mesomeric effect value and standardized result of effect quantity | | | | |
|---|---|---|---|---|
| - | H | | I | |
| Category | Direct effect | Indirect effect | Direct effect | Indirect effect |
| Mediation Path | Knowledge acquisition | | | |
| Effect | 0.23 | 0.14 | 0.16 | 0.15 |
| Standard Error | 0.08 | 0.05 | 0.07 | 0.06 |
| $p$ | 0.01 | 0.01 | 0.02 | 0.01 |
| Effect size | 62.54% | 37.46% | 52.74% | 47.26% |

Table 7 clearly shows that the results of the Goodness of Fit (GFI) test value of the model in Fig. 3 are 2.98, the GFI is 0.93, the TLI is 0.92, the Root-Mean-Square Error of Approximation (RMSEA) Deviation is 0.07, and the Standardized Root Mean Square Residual (SRMSR) is 0.05. The results indicate that each aligns with the actual conditions, suggesting that the mediation model has a high degree of fitness and credibility. Therefore, the Mesomeric effect value and effect amount obtained on this basis indicate that the result for the indirect path 1 is significant. At this time, the Mesomeric effect value is 0.14, the $p$ value is less than 0.05, and the effect amount reaches 37.46%. The direct Effect size of direct effect 1 is 0.23, so the use of an intermediary work-oriented SME for knowledge acquisition will impact employees innovation performance and, in turn, employee motivation. Hypothesis J6 is verified. In addition, the Mesomeric effect value of indirect path 2 is 0.15, and the $p$ value is less than 0.05. The direct Effect size of direct effect 2 is 0.16, so the use of a socially oriented SME, which serves as an intermediary in knowledge acquisition, will impact employees innovation performance and, in turn, employee motivation. Hypothesis J7 is verified.

## 5. Conclusion and Outlook

### 5.1. Conclusion

To examine the relationship between knowledge-based SME usage and employee motivation, this study employed data analysis techniques to propose and test relevant hypotheses. Experimental results demonstrated that the MARO-FP algorithm performed effectively, with running time decreasing sharply as minimum support increased (from over 1,000 seconds to approximately 50 seconds at a minimum support of 0.5). The algorithm achieved an RMSE below 20% and maintained an acceleration ratio consistently above 0.9, outperforming baseline methods. Field investigation confirmed that both work-oriented and social-oriented SME usage significantly enhanced employee innovation performance and motivation, with knowledge acquisition playing a significant mediating role. All proposed hypotheses were supported, and the algorithm effectively uncovered the relationship between SME use and employee motivation. To address potential employee resistance, organizations should adopt transparent communication about monitoring practices and provide training to help employees use SME constructively.

### 5.2. Management Decision Insights

The findings offer the following implications for managerial decision-making. First, managers should shift from restrictive to guiding SME policies, encouraging knowledge sharing and interaction. Second, incentive systems should publicly recognize knowledge contributions, combining material and spiritual rewards. Third, SME platforms should be integrated into knowledge management systems to convert user-generated content into formal knowledge assets. Fourth, platforms with social functions can be introduced to promote cross-departmental communication through online activities. Fifth, training programs should include modules on efficient SME use and information integration. In summary, managers should shift from passive responses to actively utilizing SMEs for policies, incentives, knowledge management, communication, and training, using them as a tool to enhance knowledge acquisition and incentives and to create a more open and innovative organizational environment.

### 5.3. Future Outlook

The findings contribute to the literature by expanding the application framework of SME in management and clarifying the differentiated effects of usage purposes. However, the study has limitations: it did not examine platform-specific effects (e.g., LinkedIn vs. Facebook) or consider potential moderators such as employee engagement, job satisfaction, or gender. Future research should investigate these factors to provide a more comprehensive understanding of how SME influences employee motivation across diverse contexts.

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**Declaration of Artificial Intelligence (AI) Tools**

The author confirms that no AI tools were used in the preparation of this manuscript. This paper did not utilize any artificial intelligence tools to generate scientific ideas, research methods, data interpretation, analysis, conclusions, or academic arguments. The author has reviewed the manuscript and is fully responsible for all of its contents.

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**Appendix**

Algorithm 1 outlines the complete steps of MARO-FP, including input, output, ontology preprocessing, FP-tree construction, multi-level frequent itemset mining, and redundant rule pruning.

Algorithm 1 MARO-FP (Multi-level Association Rule Mining with Ontology and FP-tree)

Input: Transaction database $D=\{T_1,T_2,\ldots,T_n\}$, where each transaction $T$ is a set of items; Ontology $O$; Minimum support thresholds $\mathrm{minSup}\ell$; Minimum confidence threshold $\mathrm{minConf}$.

Initialization: Expanded transaction set $D' \leftarrow \varnothing$; Set of frequent itemsets $F \leftarrow \varnothing$; Set of association rules $R \leftarrow \varnothing$.

Main Steps:

for each transaction $T \in D$ do
    $T' \leftarrow \varnothing$
    for each item $i \in T$ do
        if $i \notin O$ then continue
        $T' \leftarrow T' \cup \{i\}$
        ancestors ← GetAncestors $(i,O)$
        $T' \leftarrow T' \cup$ ancestors
    end for
    $D' \leftarrow D' \cup \{T'\}$
end for
Scan $D'$ to compute count$(i)$ for each item $i$
Determine the level $\ell = \mathrm{Level}(i)$ for each item $i$ using $O$
Build FP-tree:
    $L$ ← list of frequent items sorted in descending order of support
    Create root node of FP-tree $root$
    for each transaction $T' \in D'$ do
        filtered ← items in $T'$ that appear in $L$, sorted according to $L$
        Call $\mathrm{InsertTree}(\mathrm{filtered}, root)$ (standard FP-tree insertion)
    end for
Call $\mathrm{FPGrowth}(root,\varnothing)$ to mine all frequent itemsets satisfying level-specific support thresholds and add them to $F$
for each frequent itemset $X \in F$ with $|X| \geq 2$ do
    for each non-empty subset $A \subset X$ do
        $B \leftarrow X$ , $A$
        $\mathrm{conf} \leftarrow \frac{\mathrm{support}(X)}{\mathrm{support}(A)}$
        if $\mathrm{conf} \geq minConf$ then
            $R \leftarrow R \cup \{A \Rightarrow B\}$

        end if
    end for
end for
Filter redundant rules:
    for each rule $r$ : $A \Rightarrow B \in R$ do
        if rule $r$ satisfies Definition 1 (some item is an ancestor of another item in the rule) then
            remove $r$ from $R$
        else if there exists a rule $r'$ : $A' \Rightarrow B' \in R$ such that Definition 2 holds
            (each item in $A'$ is an ancestor or equal to the corresponding item in $A$, similarly for $B'$, and $\mathrm{conf}(r)$ lies in the expected confidence interval of $\mathrm{conf}(r')$ then
            remove $r$ from $R$
        else if there exists a rule $r'$ : $A' \Rightarrow B' \in R$ with $A \subset A'$ and $B' = B \cup (A',\ A)$ such that Definition 3 holds
            (no significant difference between $\mathrm{conf}(r)$ and $\mathrm{conf}(r')$ then
            remove $r$ from $R$
        end if
    end for
return $R$
Output: Set of multi-level association rules $R$