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Research Article

Assessing the Complex Interplay of China's Fertility Policy Adjustments and Female Employment Dynamics: An In-depth Analysis of the Digitalized HRM Landscape in the Age of AI and Big Data

Jiayue Zhang [1*], Rossilah Jamil [2]

[1] Ph.D candidate, Azman Hashim International Business School, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia
[2] Associate Professor, Doctor, Azman Hashim International Business School, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia
* **Corresponding Author:** zhangjiayue@graduate.utm.my

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ABSTRACT

The fertility policy adjustments are occurring against a backdrop of rapid technological advancement, characterized by the integration of big data analytics and artificial intelligence (AI) into human resource management (HRM) practices. In the banking sector, as in many other industries, the adoption of these technologies has become increasingly pervasive. This study explores the intricate relationship between fertility policy adjustments, the integration of big data and AI in HRM practices, and employee satisfaction within China's banking sector. In response to evolving demographic and technological landscapes, the research aims to uncover how fertility policy adjustments influence female employment dynamics, the adoption of big data and AI in HRM, and ultimately, employee satisfaction. Utilizing a quantitative research design, structured surveys were administered to female bank employees. The resulting data were rigorously analyzed using the Statistical Package for the Social Sciences (SPSS). The study underscores the practical significance of optimizing HR technologies, particularly big data analytics and AI, for enhancing both HR functions and employee satisfaction. It also emphasizes the importance of data-driven HR practices and predictive employee retention strategies as crucial tools in creating responsive and supportive work environments. Additionally, this research contributes to HRM theory by recognizing the pivotal role that technology integration plays in shaping modern HR strategies and organizational success. While acknowledging its limitations, this study lays the foundation for future research, including studies that are longitudinal, comparative, and qualitative studies, to offer a more comprehensive understanding of the complex dynamics in the contemporary workplace.

Keywords: Fertility Policy Adjustments, Digitalized HRM Landscape, Female Employment Dynamics, Utilization of AI and Big Data, Employee Satisfaction.

INTRODUCTION

Big data and artificial intelligence (AI) have transformed global businesses and organizations. Technology has made business operations more efficient and introduced new employee engagement and management tools. Big data and AI in human resource management (HRM) may enhance performance assessment, recruit top personnel, and foster a well-being-focused workplace. It investigates how firms use these technologies and how they impact employee satisfaction. Technology and culture are rapidly affecting the workforce (Tongkachok et al., 2022). The transition is affected by reproduction regulations, female labor force participation, AI and big data use, and employee happiness. Populations have been influenced by fertility regulations (H. Cheng, Ma, Qi, & Xu, 2021). Due to society's changes, these regulations have been revised. This study examines policy reforms' implications on women's labor force participation (Aracil-Jordá, Clemente-Almendros, Jiménez-Zarco, & González-González, 2023). A complicated network of fertility policy and female employment dynamics influences women's career choices, job stability, and economic involvement.

Big data analytics demonstrates conception-related female labor force swings. Data have always existed and have always been analyzed in a complex way (Azevedo & Reis, 2019). This explains how fertility regulations affect work schedules (De Vries, Bliznyuk, & Pinedo, 2023). Changing fertility regulations affect the working-age population and dependence ratio, affecting the economy. Big data and AI can mimic fertility policy economic consequences for policymakers and economists. Estimating the labor market and allocating resources need assistance (Perini, Batarseh, Tolman, Anuga, & Nguyen, 2023). Due to changing birth rates and age distributions, these technologies are vital for healthcare planning since they predict and address future demands. Changing fertility restrictions affects women's professional conduct, affecting the number of working women. Maternity leave, daycare, and work-life balance regulations affect women's career choices and family life (Pal & Shekhar, 2021). Childcare help and robust maternity leave rules might encourage women to work, increasing their workforce participation. Without these regulations, women may have to delay or forgo children to pursue their careers. Maternity and parental leave, as well as pregnancy and delivery discrimination protections, can affect women's career stability (Heymann et al., 2019). Thus, these restrictions affect female workers' job security. Reproduction policy changes may perpetuate gender inequality and restrict women's job advancement (Baniel et al., 2023). These policies have significant economic effects on economic stability and family income.

Different fertility policies affect employee happiness and numerous work environment factors. Promoting work-life balance is obvious. Quansah, Ohene, Norman, Mireku, and Karikari (2016) is cited. Family planning strategies like flexible work schedules and parental leave help employees balance work and life. Fewer conflicts between work and life reduce stress and boost job satisfaction (Henriques, Marcenaro-Gutierrez, & Lopez-Agudo, 2020). Fertility policies that provide job stability during maternity or paternity leave boost employee satisfaction. The issue is twofold. Before then, little was known about the complicated linkages between fertility policy changes and women's social roles, including job stability, professional choices, and economic participation. In digitalized human resource management, little is known about how shifting fertility policies affect talent management, employee engagement, and work-life balance. It's unclear how HRM technology can help human resource management. Given the constant changes in industries and businesses caused by automation and big data analytics, it is crucial to link these technologies to employee satisfaction in Human Resource Management (HRM). This entails examining how data-driven decision-making might improve workplace culture, performance appraisals, and recruiting to improve employee health and satisfaction. This essential research effort seeks to understand the complicated links between reproductive limitations, female work dynamics, big data and AI, and job satisfaction. Emphasizing digitalized HRM settings' intermediate role in this complicated system achieves this. Multiple goals motivate this study.

This research evaluates company human resource management techniques using AI and big data analytics. Big data analytics, artificial intelligence, and efficient data management can all be used to achieve business intelligence and better decision-making (Ye & Jonilo, 2023). Due to technology's constant change, understanding how it's used in employee engagement, performance management, and recruiting is crucial. The research seeks to fully describe how HRM is changing in the digital age. This research also evaluates employee well-being and work satisfaction. This study examines how fertility policy and HRM practises affect employee happiness and experiences. Work-life balance, job happiness, and well-being will be examined to see how these policies and technology affect the workforce. The research intends to examine how digital HRM settings mediate. It seeks to understand policy, technology, and employee experiences by recognizing these complicated links. Its ability to affect governance at several levels makes this extensive study noteworthy. This study impacts organizational and national policymakers. Policymakers may develop gender equality, family assistance, and labor productivity measures by understanding the intricate links between reproductive policy changes, digitalized HRM practices, and employee happiness.

Technology impacts HRM and fertility policy, thus studying them is crucial. These realities must be considered by businesses seeking productivity and efficiency. The article examines how digitalized HRM, big data analytics, and AI may improve performance management, talent acquisition, and worker productivity. The study contributes to HRM digital transformation discussions. In this age of rapid technological change, companies must understand how to employ AI and big data for HR goals. This study expands academic understanding of labor dynamics, technological integration, human resource management, and technology integration by setting the framework for future research.

LITERATURE REVIEW

Fertility Policy Adjustment and Employee Satisfaction

Modern companies recognize the need to create a work-life balance for their employees since employee satisfaction is important to a firm's success. This support requires fertility policy adjustments that offer a variety of benefits to fulfil employees' family planning needs. Lieber, Clarke, Kinra, Nadal, and Thampi (2023) found that paid parental leave changes fertility policy. Employees who have broad maternity leave benefits are happier, showing that they cherish the chance to spend time with their babies without financial worries. Khalid and Martin (2017) found that telecommuting and decreased workweeks boost employee contentment. These instructions teach employees how to address infertility issues while maintaining a work-life balance. Borsa and Bruch (2022) found that fertility treatment financing influences fertility policy. Reproductive therapy benefits from employers affect workers' stress and job satisfaction. It is important to note that reproductive policy changes may affect employee pleasure differently by gender. Asai and Koustas (2023) say these measures benefit women more since they have greater career and familial duties. These initiatives boost job satisfaction and family participation, which men appreciate. Fertility rules promote employee satisfaction and create a more unified and supportive workplace for businesses and employees.

H1: Fertility policy adjustments have a significant and positive impact on employee satisfaction.

Fertility Policy Adjustment and Utilization of Big Data and AI

Organizations across various sectors are using big data and AI to improve operations, make better decisions, and gain a competitive edge. Several companies have reassessed their fertility policies to help employees, recognizing the importance of employee satisfaction. Employee productivity is affected by reproductive policy changes like flexible work options and paid parental leave. Conforming employees are more productive, according to Aldabbas, Pinnington, and Lahrech (2021). Big data and AI may be used more effectively when work-life balance is improved, which decreases employee stress and helps them focus on their tasks. AI for parental help is a novel idea. Chatbots and smart AI-powered apps embedded into the company's infrastructure may teach employees about alternative childcare, maternity leave, and reproductive drugs. Klipstein et al. (2022) found that it speeds up resource acquisition and boosts employee satisfaction. Big data analytics is needed to predict societal effects of reproductive policy changes. These rules may be evaluated using data analytics to analyze employee happiness, retention, and work-life balance. Big data analytics streamlines fertility processes to benefit staff (Zhang, Zang, Zhu, Uddin, & Amin, 2022). AI algorithms are customizing employee benefit packages, including reproductive benefits. This personalization tailor benefits like flexible work hours and reproductive treatment aid to workers.

H2: Fertility policy adjustments have a significant and positive impact on the utilization of AI and big data.

Fertility Policy Adjustment and Female Employment Dynamics

Modifying fertility policy aims to increase and maintain female employment participation. Qureshi, Harris, and Atkinson (2016) states that women are more inclined to work for organizations with paid maternity leave and on-site child care, according to research. These activities encourage work-life balance for women. Reproductive policy changes affect firm leadership and female labor force participation. Supportive fertility policies help women become leaders. These rules promote work-life balance and encourage women to become leaders, promoting a fair and inclusive workplace. Corporations' broad fertility plan use indicates their gender diversity and inclusion efforts. By emphasizing fertility help, companies attract more women and demonstrate their commitment to a diverse and inclusive workplace. The company's reputation and employer brand increase. Boguszewski, Woods, Ducar, and Taylor (2022) found that favorable reproduction policies increase the number of women promoted to top positions in enterprises. These regulations show an organization's commitment to diversity and inclusion by giving women more career growth possibilities. Fertility policy may affect socioeconomic status, ethnicity, and geography. Chen and Fang (2021) recommend incorporating intersectionality into fertility program design and implementation to accommodate the specific needs and challenges of diverse women groups.

H3: Fertility policy adjustments have a significant and positive impact on female employment dynamics.

Fertility Policy Adjustment and Digitalized HRM Landscape

Digital HR management has transformed staff management. Adapting fertility policies to workers has also gained recognition. This literature review examines how fertility policy changes affect digitalized human resource management and these two occurrences. Due to fertility policy changes, HRM systems with fertility data have greatly influenced digitalized HRM. Melash et al. (2023) report that HRM software is increasingly tracking reproductive benefit utilization, including parental leave and fertility therapy. This organization helps HR administrators make data-driven decisions by monitoring policy efficacy. The digitization of HRM allows employee benefit customization. AI-driven algorithms can change fertility policies, such as family planning and employee flexibility. Salinas and Jorquera-Samter (2021) show how AI-driven support systems educate and empower fertility policy adjusters. Digital HRM solutions provide real-time tracking of employee well-being, including fertility policy engagement. It has been found that corporations use digital platforms for employee feedback and sentiment analysis on these rules. This constant feedback loop lets HR departments quickly alter policies to meet workers' needs.

H4: Fertility policy adjustments have a significant and positive impact on the digitalized HRM landscape.

Digitalized HRM Landscape as a Mediator

Digital HR management has transformed personnel management. The digitalized HRM environment may simply absorb fertility policy changes. Digital HRM systems help companies integrate and promote reproductive benefits, according to Ogbeibu, Pereira, Emelifeonwu, and Gaskin (2021). Benefits include flexible work hours, fertility treatment coverage, and paid maternity leave. This relationship makes these benefits more visible to employees. Human resource management digitalization enables personalized employee experiences, which boosts employee happiness. Jiang and Bormann (2023) suggest that AI-driven algorithms can adapt reproduction plans to worker preferences. These systems match reproductive benefits to employees' family planning goals by analyzing employee data and preferences, enhancing employee happiness. Organizations can evaluate employee fertility policy input using digital HRM systems. Aman-Ullah, Ibrahim, Aziz, and Mehmood (2022) examine how digital platforms affect employees' policy experiences. Thanks to this feedback loop, HR departments can quickly address problems and alter policies to meet employee expectations. Digitalized HRM helps lawmakers make productive decisions using data. Guest (2017) shows that big data analytics may help organizations understand how these restrictions affect employee satisfaction. Businesses can improve fertility policies using this data. Digitalized HRM aids fertility policy changes and employee happiness. Digital HRM solutions improve employee experience by tailoring work standards, improving communication and accessibility, collecting feedback, and allowing data-driven decision-making.

H5: Digitalized HRM landscape mediates the relationship between fertility policy adjustments and employee satisfaction.

HR systems in digital HRM must quickly accommodate fertility policy changes. Digital HRM systems inform workers about fertility benefits such as paid maternity leave, flexible work arrangements, and reproductive treatment coverage (Radonjić, Duarte, & Pereira, 2022). This link lets workers use these benefits and HR track their performance. Big data and AI-integrated HRM provides fertility policy efficacy insights. According to Ha (2022), organizations use data analytics to assess how laws affect employee happiness, retention, and workforce dynamics. Data-driven efforts can enhance employee fertility policy. Digitalized HRM systems may change reproductive benefits using AI. It has been found that AI can analyze vast datasets to create fertility programs for each employee. Customized family planning benefits make employees happier and more inclined to use the program.

H6: Digitalized HRM landscape mediates the relationship between fertility policy adjustments and utilization of AI and big data.

HRM systems have improved to provide specific support to female employees, notably in reproductive planning. Moore, Durst, Ritter, Nobrega, and Barkema (2020) emphasize the relevance of AI systems in these platforms, which may correctly personalize reproductive medicines to female employees' needs and family planning goals. Customization improves administrative efficiency and ensures that reproductive benefits are tailored to individual choices, increasing work satisfaction and commitment. Digitalized HRM solutions are being used to measure female employees' reactions when fertility policy changes. Ma, Ollier-Malaterre, and Lu (2021) recommend adopting online platforms to collect female employee feedback in a continuous loop. This technique encourages involvement in decision-making and helps companies understand and meet the needs of their female employees. This type of feedback mechanism allows enterprises to quickly address issues, make changes, and create policies that match the needs of their female employees. Digitalized HRM settings provide real-time feedback and give a plethora of information for fertility strategy decisions. This data-driven strategy ensures that organizations' strategic decisions are founded on a deep awareness of their female workforce's preferences and demands. Thus, reproductive programs work better, creating a company culture that values employee well-being. To conclude, AI and Digitalized HRM systems help design fertility programs for female employees. Through online feedback channels, organizations may react to changing needs and actively create policies that benefit their female employees.

H7: Digitalized HRM landscape mediates the relationship between fertility policy adjustments and female employment dynamics.

Based on the above discussion and literature we developed the following conceptual framework as shown in **Figure 1**.

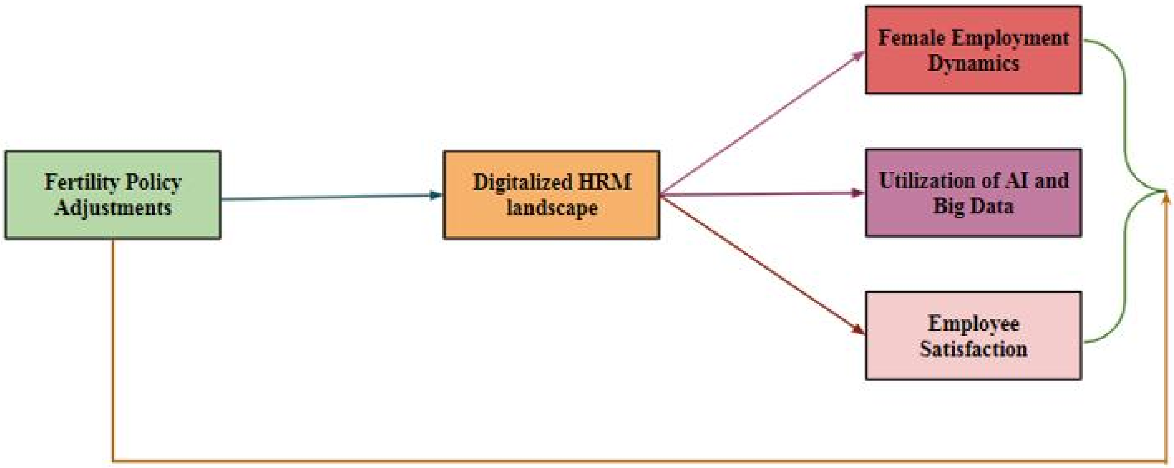

Figure 1. Conceptual Framework

METHODOLOGY

This study collected and analyzed data quantitatively. This method required analyzing the complex relationships between reproductive restrictions, female work patterns, big data and AI, and employee happiness. Systematic surveys and statistical analysis provide extensive dataset analysis. Women in China's banking business were chosen for this study because of their economic importance. Banking institutions' role in China's financial industry helps explain the labor environment and reproductive limits on women.

The appropriate sample size for finite populations was discovered using Cochran's approach. With a 95% confidence interval and a 5% error margin, a minimum sample size of 384 was set to account for the expected number of Chinese female bank personnel. A 430-person sample was used to boost research reliability and adjust for non-respondents. Due to practical difficulties in reaching the banking demographic, convenience sampling was used. This technique chose participants based on availability and desire to participate. Thorough statistical analyses were undertaken to confirm the study's integrity and reduce bias.

Personal distribution of standardized questionnaires to female bank workers collected data. The surveys collected data on work satisfaction, HRM, and fertility policy. Personal contacts helped us receive precise replies and speed up explanations, enhancing data quality and dependability. Data was evaluated carefully in the Statistical Package for the Social Sciences (SPSS). The program supports several statistical approaches, making it ideal for quantitative research. Dataset patterns, relationships, and trends were detected using descriptive statistics, correlation, and regression. This lengthy study shows how fertility policy and HR management reforms impact employee happiness. The inquiry emphasized ethics. All participants gave voluntary consent and understood the study's aims under informed consent criteria. All specific information was deleted to protect participants' responses and personal data. Many biases and conflicts of interest disappeared. The study conducted a full ethical examination and obtained institutional authorization to demonstrate its commitment to ethical research.

FINDINGS

Descriptive Statistics

Table 1 and **Figure 2** display descriptive statistics for five variables: Fertility Policy Adjustments (FPA), Digitalized HRM Landscape (DHRM), Female Employment Dynamics (FED), Utilization of AI and Big Data (UAIBD), Employee Satisfaction (ES), generated from 430 observations. The average rating for each variable among respondents was given by the mean, which is a measure of central tendency: FPA had a mean score of 3.76, DHRM 3.86, FED 3.82, UAIBD 4.00, and ES 3.87. The standard deviation, which measures data spread, shows that FPA has the largest variability at 1.123, while UAIBD has the lowest variability at 0.966. Notably, each variable's response range is constrained to a range between 1 and 5, with 1 being the minimum and 5 being the maximum. When skewness is examined, it is clear that all variables have a little leftward skew (negative skewness), indicating that responses tend to cluster toward the higher end of the scale. Additionally, kurtosis values that are close to zero show that neither the heavy-tailed nor the light-tailed distributions are present in the data distributions, which closely approximate a normal or mesokurtic form.

Table 1. Descriptive Statistics

	N total	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
FPA	430	3.76	1.123	1	5	-.823	-.003
DHRM	430	3.86	1.011	1	5	-.828	.281
FED	430	3.82	1.108	1	5	-.834	.165
UAIBD	430	4.00	.966	1	5	-.946	.565
ES	430	3.87	.968	1	5	-.717	.402

Note: FPA=Fertility Policy Adjustments, DHRM=Digitalized HRM Landscape, FED=Female Employment Dynamics, UAIBD=Utilization of AI and Big Data, ES=Employee Satisfaction.

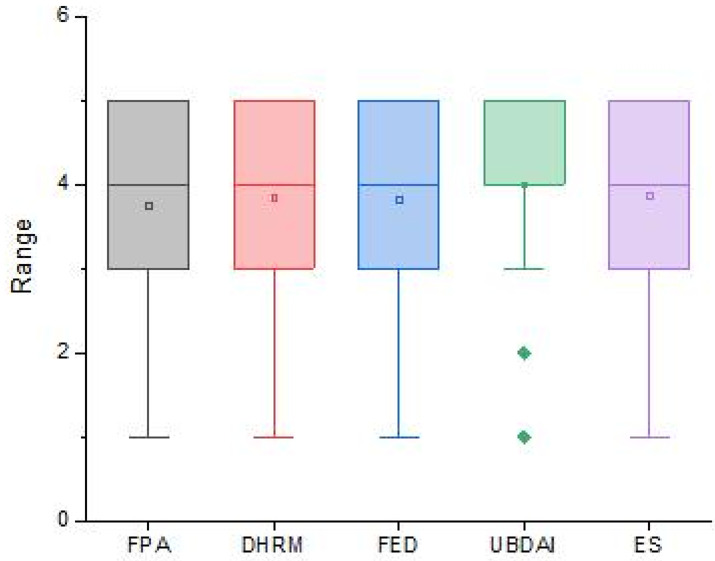

Figure 2. Descriptive Statistics

Reliability Analysis

Table 2 displays the findings of a reliability analysis on five distinct variables: FPA, DHRM, FED, UAIBD, and ES, each with a set number of items. The accuracy and precision of the measurement tools used to measure these variables must be evaluated through this study. Starting with FPA, which consists of four elements (FPA1, FPA2, FPA3, and FPA4), the outer loading values vary from 0.544 to 0.838. These outer loadings represent the degree to which each item corresponds with the entire FPA construct. The Cronbach's alpha coefficient for FPA is 0.872, indicating that the items have a high level of internal consistency. The next set of data is DHRM, which consists of four items (DHRM1, DHRM2, DHRM3, and DHRM4) with outer loading values ranging from 0.670 to 0.763. While the outer loadings have reasonably good associations with the overall construct, Cronbach's alpha coefficient for DHRM is slightly lower at 0.695, indicating that internal consistency among these items might be improved.FED, which has five parts (FED1, FED2, FED3, FED4, FED5), has outer loading values from 0.590 to 0.837. A Cronbach's alpha coefficient of 0.791 indicates good internal consistency among FED's employee feedback items. UAIBD has five components with outer loading values from 0.611 to 0.748. (UAIBD1, UAIBD2, UAIBD3, UAIBD4, UAIBD5). UAIBD has a Cronbach's alpha coefficient of 0.862, indicating a good level of internal consistency among the items testing understanding and application of international business principles. A total of five components (ES1, ES2, ES3, ES4, ES5) with outer loading values ranging from.578 to 786 make up ES. The Cronbach's alpha coefficient for ES is 0.854, indicating that the items measuring employee satisfaction have strong internal consistency.

Table 2. Reliability Analysis

Variable	No. of items	Items	Outer Loading	Cronbach's Alpha
FPA	4	FPA1	.685	0.872
		FPA2	.544	
		FPA3	.838	
		FPA4	.800	
DHRM	4	DHRM1	.718	0.695
		DHRM2	.763	
		DHRM3	.670	
		DHRM4	.722	
FED	5	FED1	.829	0.791
		FED2	.780	
		FED3	.829	
		FED4	.590	
		FED5	.837	
UAIBD	5	UAIBD1	.652	0.862
		UAIBD2	.611	
		UAIBD3	.748	
		UAIBD4	.720	
		UAIBD5	.717	
ES	5	ES1	.708	0.854
		ES2	.786	
		ES3	.670	
		ES4	.757	
		ES5	.578	

Note: FPA=Fertility Policy Adjustments, DHRM=Digitalized HRM Landscape, FED=Female Employment Dynamics, UAIBD=Utilization of AI and Big Data, ES=Employee Satisfaction.

Correlation Analysis

Five variables—Fertility Policy Adjustments (FPA), Digitalized HRM Landscape (DHRM), Female Employment Dynamics (FED), Utilization of AI and Big Data and (UAIBD), and Employee Satisfaction (ES)—were correlated, and the results are presented in **Table 3** and **Figure 3**. Pearson correlation coefficients, two-tailed significance values, and sample sizes (N) are displayed in the table's individual cells. Starting with FPA, it shows a substantial positive connection with DHRM, FED, UAIBD, and ES (r=0.647, p 0.01, 0.556, p 0.01, 0.504, p 0.01 and 0.501, p 0.01, respectively). These correlations show that FPA is positively correlated with each of these factors, suggesting that as FPA rises, so do the use of big data and artificial intelligence, the dynamics of female employment, and employee satisfaction. Similarly, DHRM has strong positive correlations with FED (r=0.600, p 0.01), UAIBD (r=0.533, p 0.01), and ES (r=0.503, p 0.01), indicating that as the Digitalized HRM Landscape improves, so do Female Employment Dynamics, Big Data and AI Utilization, and Employee Satisfaction. Moving on to FED, it has a strong positive connection with both ES and UAIBD (r = 0.551, p 0.01) and r=0.607, p 0.01, respectively. This suggests that when female employment dynamics improve, big data and artificial intelligence usage, as well as employee satisfaction, rise in lockstep. Furthermore, UAIBD and ES show a significant positive association (r=0.487, p 0.01), showing that as Big Data and AI usage grows, so does employee satisfaction.

Table 3. Correlation Analysis

		FPA	DHRM	FED	UAIBD	ES
FPA	Pearson Correlation	1	.647**	.556**	.504**	.501**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	430	430	430	430	430

		FPA	DHRM	FED	UAIBD	ES
DHRM	Pearson Correlation	.647**	1	.600**	.533**	.503**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	430	430	430	430	430
FED	Pearson Correlation	.556**	.600**	1	.607**	.551**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	430	430	430	430	430
UAIBD	Pearson Correlation	.504**	.533**	.607**	1	.487**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	430	430	430	430	430
ES	Pearson Correlation	.501**	.503**	.551**	.487**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	430	430	430	430	430

**. Correlation is significant at the 0.01 level (2-tailed).

Note: FPA=Fertility Policy Adjustments, DHRM=Digitalized HRM Landscape, FED=Female Employment Dynamics, UAIBD=Utilization of AI and Big Data, ES=Employee Satisfaction.

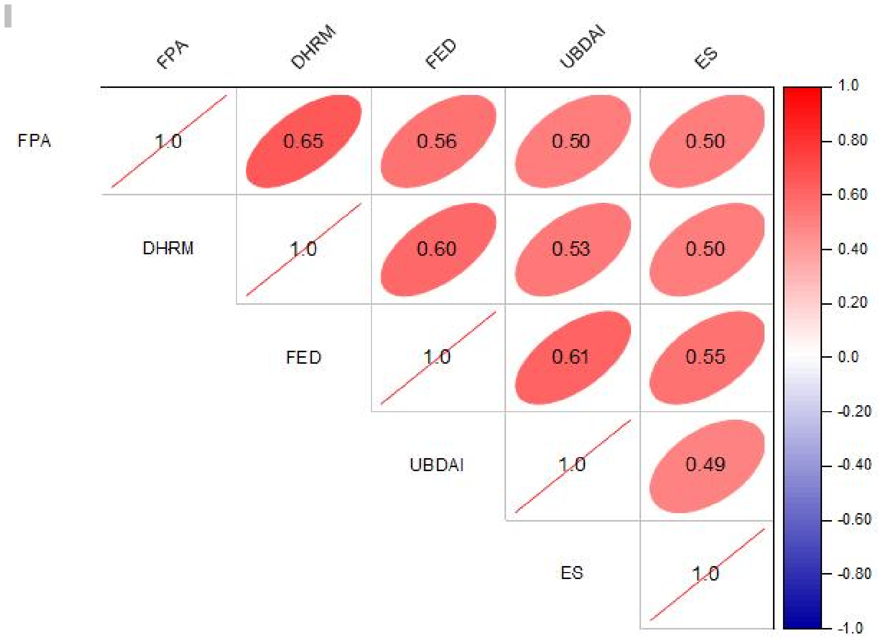

Figure 3. Correlation Matrix

Direct Hypotheses Testing

Table 4 and **Figure 4** display the findings of a regression analysis that investigated the correlations between many key organizational characteristics. It specifically looks at how changes to Fertility Policies (FPA) affect a range of dependent variables, such as Employee Satisfaction (ES), Utilization of AI and Big Data (UAIBD), Female Employment Dynamics (FED), and Digitalized HRM Landscape (DHRM). All relationships are assessed using the BETA coefficient, T-value, and P-value. A statistically significant and positive connection exists between FPA and ES in H1. BETA coefficients show that FPA increases employee satisfaction by 0.424 units. This finding's high T-value of 12.041 and low P-value of 0.0001 imply a meaningful link. We accept H1 that Fertility Policy Adjustments boost employee satisfaction. H2 demonstrates a substantial positive correlation between FPA and UAIBD. Fertility policy changes dramatically, boosting the use of Big Data and AI with a BETA coefficient of 0.445, a T-value of 12.667, and a P-value of 0.0001. As H2 is approved, firms utilizing FPA may leverage more big data and AI. The third hypothesis H3: FPA -> FED also exhibits a favorable correlation. FPA and FED are strongly statistically related, as indicated by the BETA coefficient of 0.538, T-value of 13.850, and P-value of 0.0001. This finding supports the notion that firms with fertility policy changes see more positive dynamics in female employment. H3 is approved as a result. Finally, H4: FPA -> DHRM demonstrates a significant and favorable relationship between FPA and DHRM. FPA have had a considerable impact on the digitization of human resource management, as indicated by the BETA coefficient of 0.583, a high T-value of 17.576, and a low P-value of 0.0001. As a result, H4 is accepted, implying that firms applying FPA are more likely to have a digitalized HRM landscape.

Table 4. Regression Analysis

Hypothesis	Relation	BETA	T-value	P-value	Decision
H1	FPA -> ES	0.424	12.041	0.0001	Accepted
H2	FPA -> UAIBD	0.445	12.667	0.0001	Accepted
H3	FPA -> FED	0.538	13.850	0.0001	Accepted
H4	FPA -> DHRM	0.583	17.576	0.0001	Accepted

Note: FPA=Fertility Policy Adjustments, DHRM=Digitalized HRM Landscape, FED=Female Employment Dynamics, UAIBD=Utilization of AI and Big Data, ES=Employee Satisfaction.

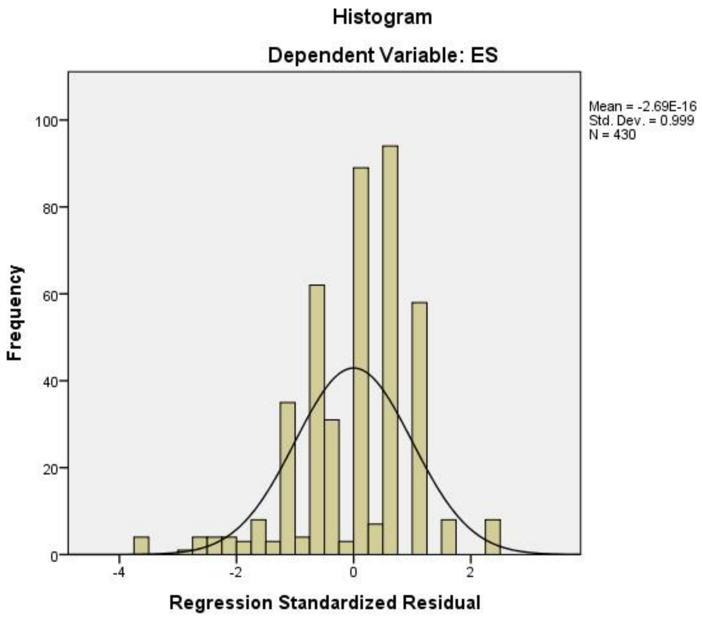

Figure 4 (a). Regression Analysis Between FPA and ES

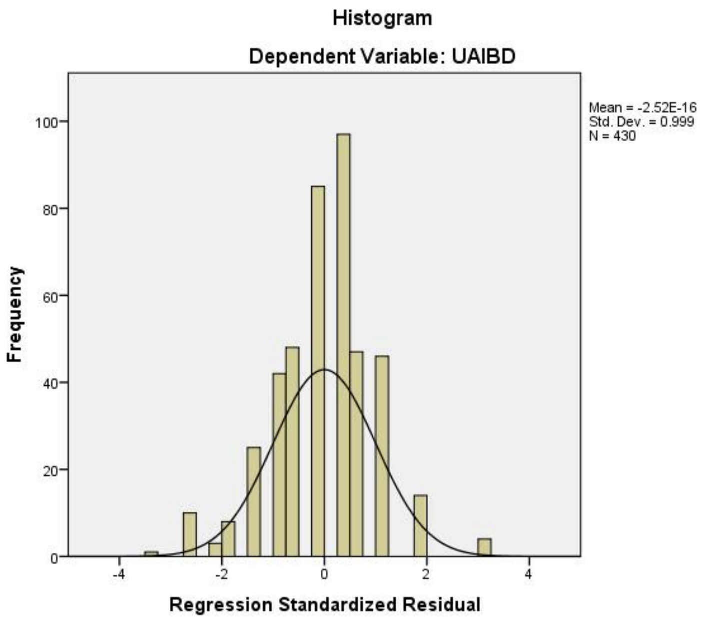

Figure 4 (b). Regression Analysis Between FPA and UAIBD

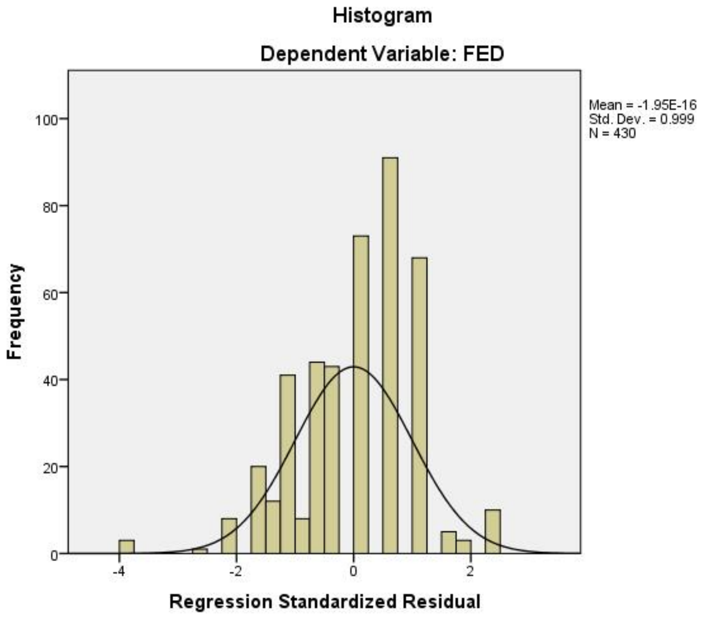

Figure 4 (c). Regression Analysis Between FPA and FED

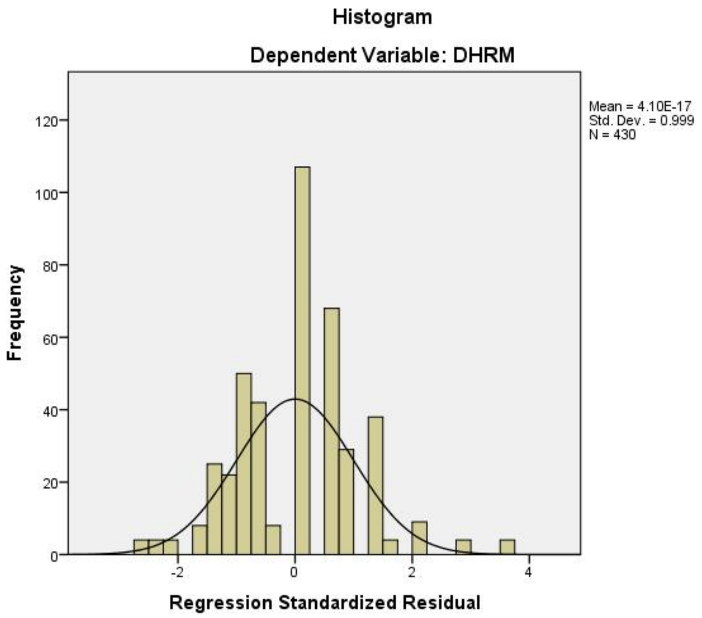

Figure 4 (d). Regression Analysis Between FPA and DHRM

Figure 4. Regression Analysis

Mediation Analysis

Table 5 shows the findings of a mediation analysis conducted to better understand the indirect effects of Fertility Policy Adjustments (FPA) on several key dependent variables, including Employee Satisfaction (ES), Utilization of AI and Big Data (UAIBD), and Female Employment Dynamics (FED), with the Digitalized HRM Landscape (DHRM) serving as the mediator. In the beginning, H5: FPA->DHRM->ES demonstrates a considerable indirect link. This implies that Fertility Policy Changes have an effect on Employee Satisfaction via the intermediary factor of DHRM. FPA improves ES with DHRM, according to the BETA coefficient of 0.172. The statistical significance of the T-value (5.606) and the low P-value (0.0001) support H5, demonstrating that DHRM may explain how FPA affects Employee Satisfaction. Following this pattern, H6: FPA -> DHRM -> UAIBD has a strong indirect effect. FPA affects big data and AI via DHRM with a BETA coefficient of 0.191. The high T-value (5.719) and low P-value (0.0001) support H6. Due to DHRM, organizations using FPA may leverage more big data and AI technology, according to this research. H7 shows a strong indirect link: FPA->DHRM->FED. A BETA value of 0.265 suggests that fertility policy adjustments improve female employment dynamics via DHRM.

The high T-value (5.723) and low P-value (0.0001) support H7. This means that firms that implement FPA, maybe as a result of an advanced DHRM, are more likely to experience favorable dynamics in female employment.

Table 5. Mediation Analysis

Hypothesis	Relation	BETA	T-value	P-value	Decision
H5	FPA -> DHRM -> ES	0.172	5.606	0.0001	Accepted
H6	FPA -> DHRM -> UAIBD	0.191	5.719	0.0001	Accepted
H7	FPA -> DHRM -> FED	0.265	5.723	0.0001	Accepted

Note: FPA=Fertility Policy Adjustments, DHRM=Digitalized HRM Landscape, FED=Female Employment Dynamics, UAIBD=Utilization of AI and Big Data, ES=Employee Satisfaction.

DISCUSSION

Multiple studies have found strong literature supporting H1. Fertility policies including reproductive medications, flexible work hours, and paid maternity leave have consistently improved female employment. Revisions to fertility policy encourage women to work. H1 and other digital technologies help women balance work and family (Abujaradeh et al., 2021). Online support groups allow people to discuss their experiences and give emotional support, while wearable devices and smartphone apps assess reproductive health. Data analytics helps companies optimize policies to meet employee needs. Changes in fertility policy have helped women advance professionally. Awoa, Atangana Ondoa, and Ngoa Tabi (2022) found that enterprises with favorable fertility policies have more women in leadership positions. Preserving female talent is vital to female employment engagement. Reproductive policy improvements including flexible work schedules and fertility insurance have been demonstrated to increase female employee retention. Digitalization streamlines benefit administration and provide instructional and training resources, Girsberger, Hassani-Nezhad, Karunanethy, and Lalive (2023) discovered. Digital technology makes fertility programs more accessible, efficient, and effective, helping women reconcile work and family planning goals. It promotes leadership gender diversity and inclusion. This analysis supports hypothesis H1 by showing that fertility policy adjustments improve female employment dynamics, and keep talented female workers in the workforce.

Hypothesis 2 implies that fertility rule modifications benefit company AI and big data utilization. Reproductive restrictions may require workforce data analysis, especially on paid parental leave and employee satisfaction. Luo et al. (2020) demonstrated how big data analytics may improve fertility policy. AI algorithms are needed to customize employee benefits, especially reproductive ones. Miles, Hutchison, and VanRaden (2023) demonstrate that AI can examine large datasets and customize fertility guidelines for employees. Fertility policy changes may need workforce data analysis, including paid parental leave and employee satisfaction. AI and big data can improve recruiting decisions for companies with modified fertility policies. This supports H2, suggesting that policy-changing corporations are AI and big data professionals.

H3 proposes that fertility rule changes boost employee satisfaction. Fertility policies like flexible work arrangements and paid parental leave help people balance work and life. Boguszewski et al. (2022) found that by employing digitalization methods like flexible work schedules and remote work, fertility policy reforms may dramatically enhance employee work-life balance. Most workers with technologically improved regulations are happier at work. Companies that follow these norms digitally see increased employee engagement and loyalty, especially among women. Digitalization gives workers access to vital family planning information and services. It also streamlines remote work and scheduling (Su, Houghton, Chen, & Zou, 2022). Fertility policy changes may help employees with family planning issues. Employer-provided insurance may help pregnant mothers financially.

H4 believes fertility rule adjustments can help digital HRM. The digitalized HRM system must smoothly handle and implement HR laws including fertility policy changes. Pan and Froese (2023) found that digital HRM systems provide reproductive benefits such as paid maternity leave, flexible work hours, and fertility treatment coverage. Organizations must analyze workforce data to alter fertility policies, especially on employee happiness and paid parental leave. Digitalized HRM introduces data-driven decision-making. Employee perceptions of these demands are collected digitally by Reibenspiess, Drechsler, Eckhardt, and Wagner (2022). Customizing employee benefit packages, including fertility incentives, requires AI-powered algorithms. This supports Hypothesis 4 which state that enterprises deploy AI-powered communication solutions in their digital HRM infrastructure to adapt to reproductive constraints.

The phrase implies that digitalized HRM influences the relationship between reproduction policy changes and female employment dynamics. Digital HRM systems integrate and manage HR needs, including fertility policy changes. These platforms help companies implement and convey fertility benefits, according to Li, Bastone, Mohamad, and Schiavone (2023). Fertility policy changes normally need staff data collecting and analysis. Digital HRM uses data-driven decision making. Digital platforms were used to collect workers' experiences with these policies by Bhupathi, Prabu, and Goh (2023). Digital HRM's data-driven approach can reveal how reproductive policies affect female labor dynamics. Digital HRM systems can design fertility-related employee benefit packages using AI-powered algorithms. Trocin, Hovland, Mikalef, and Dremel (2021) show how AI can analyze large datasets to adapt fertility guidelines for employees. The customization confirms hypothesis H5, which suggests that the digital HRM environment may improve fertility policies for female employees.

H6 links AI, big data, and fertility policy changes through digital HRM. Many companies employ digital HRM systems to manage and track these changes. Organizations must frequently review workforce-related indicators like employee satisfaction and fertility benefit use to update fertility policy. Digital HRM provides a structured basis for data collection and evaluation. Digital systems track employee responses to these limits (M. M. Cheng & Hackett, 2021). Through AI and big data, digital HRM's data-centricity may deliver significant benefits. Data shows that AI-powered HRM systems can boost fertility initiatives. Shet, Poddar, Wamba Samuel, and Dwivedi (2021) showed that AI can assess massive datasets and customize fertility rule changes for each employee. This connectivity to H6 will let the digital HRM environment employ AI to improve and tailor fertility treatments.

H7 states that the digital HRM environment mediates fertility policy changes and employee contentment. Digital HRM systems improve fertility information and communication. Employees may quickly obtain fertility policy eligibility and application information via chatbots and mobile apps. Tongkachok et al. (2022) believe that big data analytics can help organizations understand how these rules affect employee satisfaction. This data-driven strategy helps organizations analyze and enhance fertility policy changes, improving employee satisfaction and standards. AI-driven algorithms in digital HRM systems may design employee benefit packages, including reproduction incentives. Jiang and Bormann (2023) show that AI can analyze large amounts of data and customize worker fertility plans. This ensures that employee benefits match family planning goals, which may boost satisfaction. Firms can gather and evaluate fertility policy input in digital HRM settings. Bergeron (2023) says digital platforms gather employee opinions on these needs. This feedback loop helps HR departments to quickly resolve complaints and align rules with employee expectations, improving employee happiness.

CONCLUSION

This study examines the intricate interaction between fertility rules, AI, and big data in HRM, and employee happiness in the Chinese financial business. The results illuminate these components' complicated interactions, providing practical and intellectual insights. HR technology like big data analytics and AI may improve HR operations, according to the research. Modern technology may boost employee satisfaction and make banks more flexible and responsive. Data insights are important for forecasting staff retention strategies. This is essential for boosting finance talent retention methods. Technology in human resource management boosts productivity and creates a happy workplace. Its theoretical contributions go beyond practical repercussions and advocate a paradigm shift in human management and engagement through technology enhancements. Results support current thoughts on increasing organizational performance using HRM technology. Data-driven HR initiatives are essential, according to the report. This statement underlines the changing nature of human resource management and the importance of data analytics in directing organizational performance. The study is intriguing, but convenience sampling and cross-sectional methods must be considered. Future research should use long-term and comparative evaluations, qualitative methodologies, and sophisticated analytics to comprehend these complicated processes while admitting and fixing these limitations. In-depth research of the expanding interplay between fertility policy, big data, AI, and employee satisfaction may help us comprehend its effects and application in many companies.

IMPLICATIONS

Practical Implications

The research has major implications for stakeholders, particularly Chinese financial industry players. The report prioritizes human resources technology improvements in big data analytics and AI. These tools help banks streamline human resources activities. AI-powered talent acquisition systems may be tailored to attract more talent. Big data analytics may help proactive talent management by providing workforce insights. AI and big data can boost HR department productivity in numerous operational scenarios. The paper also offers ways institutions' staff might use big data and AI effectively. By using AI-powered chatbots or virtual assistants to manage HR concerns rapidly, banks may improve workplace responsiveness. Big data analytics can customize employee training to their requirements and career goals. Personalization motivates workers by improving job satisfaction and engagement. The research advises using big data and AI to predict employee retention. For prediction models, financial companies may investigate previous employee turnover patterns and characteristics. This knowledge allows financial institutions to focus on career development and address data-identified work-life balance issues to retain top talent. AI/Big Data analytics improve workforce strategy. Personnel data analysis can help banks forecast skill shortfall recruiting needs. AI algorithms may identify high-potential personnel, succession planning, and leadership development. These programs guarantee financial institutions have a broad and skilled personnel for future issues.

Theoretical Implications

This research advances HRM theory by stressing big data and AI's revolutionary potential. Empirical evidence shows these technologies affect HR, employee engagement, and talent acquisition. Technology's growing involvement in HR practices is acknowledged in this HRM theory modification, which helps us grasp modern HR dynamics. The study supports technology-integrated HR theories. It highlights how Chinese banks improve employee satisfaction and productivity with big data and AI. Technology-focused organizational success theories are supported by these findings. The study highlights data-driven HR, which is becoming increasingly popular. The study adds big data and AI applications to HR data-driven decision-making literature. This highlights HR analytics' significance in talent management and employee satisfaction. This explains data's role in current HR operations theoretically.

LIMITATIONS AND FUTURE DIRECTIONS

This study has significant drawbacks despite its usefulness. Major restrictions include convenience sampling, which may skew sample composition. Specific variations between willing participants and non-participants may affect the results generalizability. This study's cross-sectional technique only collects data once, making causation and change monitoring problematic. Longitudinal studies can reveal how fertility policy changes, HRM practices, and employee satisfaction relate. Another disadvantage is self-reported statistics. Response bias can impact self-report statistics because individuals may offer socially acceptable responses or have inaccurate memories. Future research may solve this issue by combining self-report data with objective measurements or other data sources. China's banking industry may limit the study's applicability to other industries or regions with distinct worker characteristics. Further study should explore different firms and locations to determine the importance of these findings. Findings and limitations of this study provide several intriguing research options. Academics may benefit from longitudinal research on fertility policy, HRM, and employee satisfaction. This investigation would identify trends and long-term effects of these processes. Comparisons of China and other reproduction techniques may show contextual factors that alter these links. Researching differences and similarities may provide policy recommendations and best practices. Interviews or focus groups can enhance quantitative research by studying female employees' various experiences and impressions. Qualitative research illuminates fertility policy and HRM connections in real life. Machine learning and natural language processing can enhance large data analysis. These tools reveal hidden personnel data patterns for advanced predictive modeling and customized HR interventions. Intervention studies in organizations may explore how HRM practices or policy changes enhance employee satisfaction with fertility policies. Such study can enhance HR practises with practical advice. Finally, worldwide research on reproduction policy changes, HRM, and employee happiness might provide further context. A comparative study across countries with various regulatory environments might uncover cross-cultural differences and labor management opportunities.

CONFLICT OF INTEREST

No conflict of interest was reported by the authors.

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