Analysis of Market Demand and Skills of Product Manager

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Abstract: This paper analyzes the determinants of salary levels in the modern labor market and focuses on the product manager position. Based on over 10,000 job postings from four major cities in China, this paper investigates the impact of education, work experience, company size, and city on salary levels. Through data preprocessing, dummy variable transformation, and multiple linear regression analysis, the study identifies clear patterns: salary levels increase with higher educational attainment and longer work experience; first-tier cities offer significantly higher wages than lower-tier ones; and larger enterprises generally provide better compensation structures. The city and work experience variables explain the most variance of salary differences, followed by education and company size. In addition, the analysis reveals that there are structural wage advantages for the bachelor's degree, three to five years of experience, large company employment, and city locations in Shenzhen and Shanghai, respectively. The study shows that salary formation is layered and not linear. Both theoretical and practical implications are provided. For employers, the results can guide employers to improve their hiring and retaining strategies. For job seekers, the results provide evidence based on their employment plans.

1 INTRODUCTION

In the digital age, the changing demand in the market creates new opportunities and challenges for the enterprise every day. Companies face the challenge of fulfilling customers' needs more effectively and staying up to date with the technological world. The role of the product manager (PM) is of vital importance since the manager connects technology, business, and the user, making sure that the product follows the market and the company's needs. As digital transformation accelerates, product managers are expected to go beyond functional delivery - they are now responsible for leading cross-functional teams, shaping product vision, and making strategic decisions in an uncertain environment. Luchs, Swan, and Griffin (2022) describe this shift as a form of form of 'perceptual shaping' where product managers interpret weak signals from different stakeholders and markets to proactively guide product innovation. This redefinition of the product manager's role positions them as key coordinators of digital value creation (Luchs et al., 2022).

The role of PMs has broadened due to the rapid pace of change in the Internet industry. Historically, PMs' focus on requirement management and coordination has widened to encompass data analysis, business strategy, and constant improvement. According to McKinsey, the reliance on data for both decision-making and the need to be customer-centric have greatly extended the role of the PM and made it a requisite in all . This is an important realization for PMs that they must possess an even broader skillset, one that transcends technical skills to include strategy. And it is this realization that also compels organizations to expect PMs not only to help ensure a product fits the market, but also to drive innovation and long-term business success (McKinsey, 2017).

Persistent frictions exist in the supply and demand dynamics of the product manager (PM) labour market. Job seekers often face challenges interpreting job descriptions that lack clarity or contain conflicting requirements. Conversely, employers find it difficult to select job candidates with the right skill sets and experiences. Humburg and van der Velden have in discrete choice experiments shown that employers prefer CV attributes that signal high levels of occupation-specific human capital, e.g. relevant work experience and that the job seeker's education and job tasks. Yet, employers' preferences differ and

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generic job postings might impair the clear specification of skills required. The resulting misalignment between job seekers and employers' preferences and job seekers' lack of information on employers' preferences in the PM labour market constitutes an information friction (Humburg et al., 2015).

Moreover, the variation in compensation due to factors such as job type, working environment, and individual background makes it more challenging for both job seekers and recruiters to plan effective career paths and recruitment strategies. Gazi conducted an empirical study on industrial workers and found that job satisfaction—which is influenced by factors including experience, job roles, and workplace conditions—has a significant impact on employee behavior and performance. While higher compensation may correlate with enhanced satisfaction and productivity, this relationship is also shaped by the structure and scale of the employing organization. For job seekers, especially in technical roles like product managers, understanding these variables is essential for making informed decisions; for organizations, they offer insights for building more effective incentive strategies (Gazi et al., 2024).

Against this backdrop, data-based recruitment seems to be a panacea for finding prospective employees among job seekers. Job posting data and analytics help companies refine job postings and identify potential job candidates. Peoplebox said that mining data to attract employees will help companies fill job vacancies more efficiently and hire better talent through job seekers' data and analytical results to fulfill job roles. For product managers, this approach helps identify high-frequency skill requirements and map out targeted learning paths to remain competitive in the job market (Peoplebox, 2024).

In response to these practical needs, this study systematically analyses the recruitment data for product manager positions on the BOSS Direct platform. By extracting and processing more than 10,000 job postings from 17 major cities, this study quantitatively examines the impact of four core variables: city, education level, work experience and company size on salary outcomes. Through structured preprocessing and regression modelling, this study constructs a data-driven framework that reveals the valuation logic behind product manager positions in the digital age.

This study aims to explore the impact of four dimensions, namely education level, work experience, city level, and company size, on the compensation level of product managers, and identify key patterns and thresholds that affect career development. Specifically, the study will analyze the salary differences at different educational levels (from undergraduate to master's), identify key career turning points such as 3-5 years of work experience, and evaluate the relationship between salary differences between city level and company size. The research results will provide data support for job seekers to plan their career development paths, while helping companies develop evidence-based recruitment and compensation strategies, thereby optimizing the matching efficiency of talent supply and demand in the rapidly developing labor market of the digital age.

2 LITERATURE REVIEW

2.1 Core Concepts of Market Demand

Salary level is an important indicator in the labor market that reflects the value of positions and the intensity of human resource demand. What is implied behind it is the real market demand for different types of talent. In the modern recruitment market, enterprises' demand for talent is no longer a single-dimensional match but a systematic choice based on multiple factors such as comprehensive quality, regional adaptation, job ability, and experience accumulation. At this level, salary is a holistic indicator that reflects not only individual attributes but also certain structural characteristics of the market. That is, can always find four basic variables, i.e., city, education, working experience, and company size, which have obvious impacts on salary. These four aspects are the basis of analysis of this study, attempt to empirically verify their impacts on salary and construct a quantitative model to evaluate the valuation of talents in a market-oriented environment.

As a spatial unit with highly concentrated economic resources and opportunities, cities naturally play a decisive role in job distribution and salary setting. First-tier cities usually provide higher job salaries due to their high industrial density, large number of positions, and fast development pace. Still, they also correspond to higher competition thresholds and ability requirements. In comparison, second- and third-tier cities offer relatively lower salary levels and job density, but feature lower entry barriers and less competition, making them attractive to junior professionals. These differences reflect the layered structure of urban employment markets.

Therefore, the salary differences between different cities reflect both the heterogeneity of regional economic structures and the dynamic game between job demand and talent supply. Recent empirical studies confirm this logic, for instance, urban wage premium research based on Chinese data shows that larger cities provide significantly higher wages due to agglomeration effects and industrial density (Liu et al., 2024). In addition, income disparity across cities is also shaped by labor market segmentation, which creates persistent structural barriers between different classes of jobs and regions (U.S. Census Bureau, 2023).

As an important indicator for measuring individual human capital investment, academic qualifications have always been one of the core dimensions for enterprises to screen talent. However, as the market pays more attention to practical ability and mastery of technical tools, academic qualifications are no longer the only variable that determines salary. Especially in cross-border and complex positions such as product managers, the "basic skills" and "basic operational capabilities" required for the position have gradually become important bases for companies to evaluate whether talents are competent. Therefore, companies not only pay attention to academic background, but also tend to cultivate basic capabilities with job adaptability to meet their market-oriented development needs.

Worakitjanukul conducted an empirical analysis of a large sample of data from different regions in Thailand and pointed out that education level and work experience have a significant positive impact on salary level changes, especially in cities, where workers with higher education and richer experience receive higher remuneration (Worakitjanukul, 2018). This study provides an important empirical basis for this article to explore the role of education and experience on salary.

Working years represent the accumulation of experience and the improvement of job proficiency. When recruiting, companies usually set clear experience thresholds, such as "3-5 years as a turning point", to determine whether candidates have the potential to move from execution to management. From the perspective of salary structure, years of experience are often positively correlated with salary, but whether its marginal effect continues to increase still needs to be analyzed in combination with job type and company structure.

Company size also plays an important role in the recruitment and compensation system. AmorServ pointed out in its research report that large enterprises tend to establish more systematic job classification systems and salary standards due to their abundant funds and clear management levels. In contrast, small and medium-sized enterprises focus more on immediate performance and short-term returns (AmorServ, 2024). This research result verifies the hypothetical logic of "the larger the company size, the higher the salary" proposed in this article, and highlights the deep impact of the company's organizational structure on the formulation of compensation policies.

In summary, city, education, years of work, and company size, as the four core factors affecting salary, jointly construct an evaluation system for talent value in the labor market. Understanding the inherent logic and interactive relationship of these variables is of great significance for revealing the talent supply and demand structure and compensation mechanism.

2.2 The Role of Market Demand Analysis

In a recruitment market with highly asymmetric information, market demand analysis is not only a tool for understanding employment trends but also a bridge to link job supply and talent resources. For employers, accurately grasping the changing trends of the market's requirements for job capabilities, education levels, and experience will help optimize job descriptions, adjust salary strategies, and improve recruitment efficiency. Especially in highly competitive positions such as product managers, companies can make more targeted talent selection decisions by analyzing talent portraits through data-based means.

From the employer's internal operations perspective, companies also establish targeted capability training systems and salary incentive structures through demand analysis. As a typical capability-oriented position, the salary of product managers is not only a reflection of labor income but also an evaluation tool for their performance and potential. Therefore, companies often set up a more targeted salary structure based on "actual work performance" and "position adaptation degree", thereby effectively stimulating the initiative and growth of talents. Through the feedback of this incentive mechanism, companies can promote the continuous growth of high-performance positions and optimize the overall human resource allocation. In recent years, AI has been increasingly used in human resource management to improve recruitment accuracy and organisational efficiency.Akhter, Bhattacharjee and Hasan state that AI systems help

to screen candidates, match skills to job requirements and reduce human bias in recruitment decisions. They further highlight that the use of AI is particularly effective in recruitment and performance assessment, where data-driven systems have begun to replace intuition-based decision-making, thus aligning with the broader goal of market demand analysis in optimising talent allocation (Akhter et al., 2024).

Meanwhile, for job seekers, market demand analysis has a clear career guidance function. By understanding the job density and salary levels in different cities, individuals can plan their career paths more reasonably; by mastering the relationship between education and salary, targeted human capital investment can be made; and understanding the size and development stage of different companies will help job seekers weigh the relationship between short-term returns and long-term development and make choices that are more in line with personal development goals.

At the macro level, market demand analysis provides real and dynamic data support for policymakers such as governments and educational institutions. On the one hand, it can assist in optimizing the educational structure and alleviating the mismatch between talent training and market demand; on the other hand, it can also serve as an important basis for regional human resource planning and promote the balance of employment structure between regions.

It is in this context that this study analyzes actual recruitment data, quantifies the key variables that affect salary levels, and proposes targeted suggestions based on job attributes, hoping to build a data-driven talent matching path between theory and practice.

3 METHODOLOGY

3.1 Modelling

To study the impact of different cities, education, work experience, and company size on salary levels, this paper constructs the following multiple linear regression model:

$$Average\ Salary = \alpha + \beta_1 Education + \beta_2 Years + \beta_3 Scale + \beta_4 City + \gamma Controls + \varepsilon \quad (1)$$

In this model, Average Salary is the dependent variable, indicating the median monthly salary (unit: K/K/month). The explanatory variables are defined as Table 1.

Table 1: Variable settings.

Variable	Definition
Education	Minimum education requirement for the position (e.g., college, bachelor's, master's, no requirement). The reference group is "bachelor's degree".
Years	Required work experience (e.g., no experience, 1–3 years, 4–5 years, 6–10 years). The reference group is "1–3 years".
Scale	Company size (10, 60, 300, 700, 5000, 10000 employees, etc.). The reference group is "300 people".
City	Company size (10, 60, 300, 700, 5000, 10000 employees, etc.). The reference group is "300 people".
Controls	Job categories (e.g., technical, marketing, management), used to control structural effects from different industries.
ε	The error term, representing unexplained variation not captured by the model.

The model aims to evaluate the marginal impact of the above core variables on the salary level. The categorical variables, such as education level and city level, are converted into 0/1 binary variables through dummy variables. The values of the reference group are all 0, and the values of the remaining variables are 1 for "belonging to this category" and 0 for "not belonging to this category". The reference group is selected (for example, Beijing is the reference group for the city, and undergraduate degree is the reference group for education level), and the remaining variables are converted into dummy variables and added to the model. Since the job salary is continuously distributed, ordinary least squares (OLS) is used for regression modeling. In addition, some control variables (such as job type, etc.) are also considered in the model setting to reduce the omitted variable bias.

3.2 Data Source

The data in this study comes from the BOSS direct recruitment data. From April to May 2024, more than 10,000 product manager jobs postings in 17

first- or second-line cities in China（such as Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Hangzhou, etc.）are scraped. The variables include job title, company name, salary range, education requirement, experience requirement, skill keywords, company size, job benefits, and location, etc.

This paper designed a customized data collection script in Python （Selenium + EdgeDriver）to simulate the browsing behavior of users and scrape the front-end content through XPath. After data mining, several cleaning steps were implemented by us removing the HTML tags and other unstructured characters； dealing with missing values by mean imputation or deletion, parsing salary range to extract the minimum and maximum value by regular expression, then computing the median salary as one indicator and applying the jieba word segmentation package to extract high-frequency keywords as the skill and benefits indicators. Additionally, text fields such as education and city were converted into dummy variables, and company size and experience fields were standardized to ensure consistency for modeling.

To prepare the dataset for regression analysis, must make some transformations since the two categorical variables are not numeric, so converted them into dummy variables. In this transformation, “bachelor's degree” was used as the reference group for education, and “Beijing” for the city. This paper converted each remaining category into a column taking values 0 or 1. By doing this, added qualitative variables into a quantitative model, which enhanced the statistical robustness and interpretability of our regression analysis.

4 RESULT ANALYSIS

4.1 Descriptive Statistical Analysis

This study focuses on the four core variables of education, city, work experience, and company size, and conducts descriptive statistics and variance analysis on the differences in job salaries (ANOVA tests are significant, $p < 0.001$), revealing the key influence of various factors in the workplace structure on salary formation.

In terms of education, salary levels increase with the improvement of education. Masters (19.89K) and bachelor's degrees (18.31K) are significantly higher than those with no requirements (14.63K) and college degrees (13.64K). Among them, bachelor's degrees are 4.67K higher than college degrees ($p < 0.001$), and master's degrees are 6.25K higher than college degrees ($p < 0.001$), with significant differences. However, there is no significant difference between master's and bachelor's degrees ($p = 0.36$).

Additionally, the salary distribution for the master's group shows the greatest variability, with a standard deviation of approximately 9.04 K, indicating a broad range of job levels. In contrast, the junior college group exhibits the most concentrated distribution (standard deviation 5.90 K), reflecting a more homogeneous salary structure. These patterns are clearly illustrated in Figure 1, where the wider interquartile range and more numerous outliers for the master's and undergraduate groups underscore their broader salary dispersion.

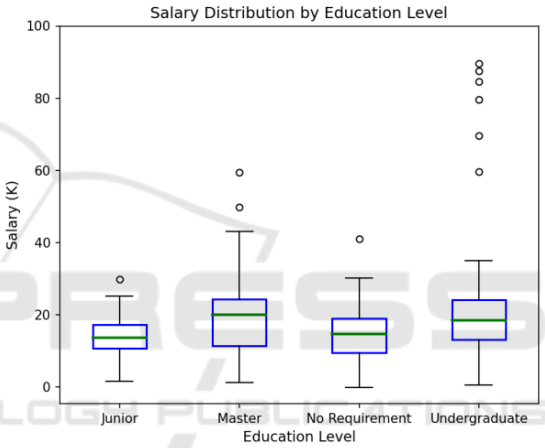

Figure 1: Salary distribution by education level.

At the city level, the overall salary distribution shows a clear gradient. Shenzhen (21.14K), Shanghai (20.98K), and Beijing (20.96K) are in the first echelon, significantly higher than other cities ($p < 0.001$), and the difference between the three is not significant ($p = 1.0$). Hangzhou (17.37K) and Nanjing (16.03K) are in the middle layer; Guangzhou (15.85K), Chengdu (14.76K), and Chongqing (12.75K) have relatively low salaries, and the largest gap between Shenzhen and Chongqing is 8.39K (+65.8%). It is worth noting that although Guangzhou is a first-tier city, its salary performance is relatively weak. Regionally, it presents the characteristics of "tiered distribution within the Yangtze River Delta, Chengdu in the Chengdu-Chongqing region is higher than Chongqing"; in terms of salary fluctuations, Shanghai has the largest standard deviation (9.05K) and Nanjing is the most concentrated (4.95K), suggesting that most jobs in the city offer salaries

closer to the media. These disparities in both central tendency and dispersion are reflected in the box plot shown in Figure 2, where outliers and interquartile ranges further illustrate city-specific wage characteristics.

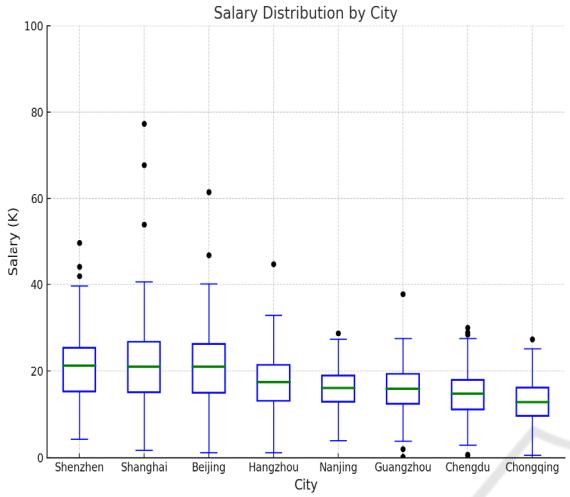

Figure 2: Salary distribution by city.

In terms of work experience, salary increases significantly with years of experience, from 15.67K for no experience to 26.83K for 6-10 years of experience, with a cumulative increase of more than 71%. Tukey test shows that salary growth is mainly concentrated in the two stages of "1-3 years" to "4-5 years" (+5.58K, $p < 0.001$) and "4-5 years" to "6-10 years" (+4.78K, $p = 0.043$), while the difference between "1-3 years" and "no experience" is not significant ($p = 0.604$), indicating that the marginal effect of initial experience accumulation is limited. These patterns are clearly illustrated in Figure 3, where the 6–10 years group shows both the highest median salary and the widest distribution, with numerous outliers indicating high-paying senior roles. In contrast, the 1–3 years group presents the most concentrated salary structure (standard deviation: 6.64 K), while the 6–10 years group exhibits the greatest variation (SD: 17.87 K). Overall, 3-5 years is the key turning point for a salary jump, and senior positions have greater salary elasticity.

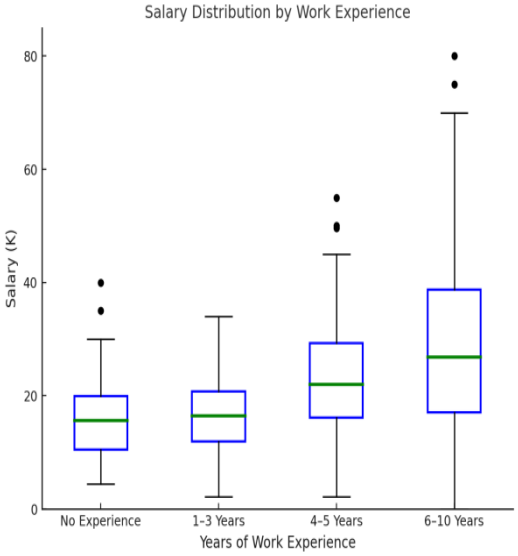

Figure 3: Salary distribution by work experience.

In terms of company size, salaries vary significantly between companies of different sizes, with an average increase of nearly 10K from 13.44K for companies with 10 employees to 23.59K for companies with 10,000 employees ($F = 34.57$, $p < 0.0001$). The scale of 300 employees is a key dividing point, with salaries significantly higher than those of companies with 60 or fewer employees ($p < 0.05$); salaries of super-large companies with more than 10,000 employees are significantly higher than those of all other groups ($p < 0.001$), reflecting their strong capacity to attract talent and offer higher-level positions.

Figure 4: Tukey HSD multiple comparisons of salary by company size.

In contrast, the salaries of micro-enterprises, with 10 employees are significantly lower. Interestingly, the analysis also reveals nonlinear patterns—for example, companies with 0 employees (e.g., self-employed entrepreneurs) report higher average salaries than some small firms, possibly due to equity incentives or profit-sharing mechanisms. Meanwhile, there are no significant differences between 700 and 5,000 people, and between 300 and 700 people, indicating that the salary structure of some medium and large companies tends to be stable, as shown in Figure 4.

In summary, education, city, work experience, and company size all significantly affect salary levels, showing hierarchical distribution and phased premium characteristics. Among those with a bachelor's degree, 3-5 years of experience, companies with 300 or more employees, and first-tier cities, job salaries are significantly better than other groups, highlighting their structural advantages in the current workplace.

4.2 Regression Results Analysis

To further explore the impact of variables such as education, city, years of work, and company size on salary, this study constructed a multivariate linear regression model and employed ordinary least squares (OLS) estimation. The results are presented in Table 2, Table 3, and Table 4. The model fits well, and the explanatory power and statistical significance of key variables are high. Under the condition of controlling other variables, years of work have a significant positive impact on salary (coefficient is 1.61, $p < 0.001$), indicating that for every two years of work experience, the average salary will increase by about 1.6K, verifying the market premium effect of experience accumulation.

The company size variable also shows statistical significance (coefficient is 0.00065, $p < 0.001$), but the impact is low, indicating that the larger the scale, the slightly higher the salary, but the actual increase is smaller, indicating that although the scale is significant, the actual explanatory power is limited.

In terms of educational background, with bachelor's degree as the reference group, the regression results show that the salary of those with a master's degree is slightly higher than that of those with a bachelor's degree (coefficient is 0.2991, $p = 0.0078$), while the salary of those with a junior high school degree and a college degree is significantly lower than that of those with a bachelor's degree (respectively -1.3826, $p < 0.001$; -0.2391, $p \approx 0.93$), reflecting that higher education has certain salary advantages in the workplace, but the difference between a master's degree and a bachelor's degree is not significant after controlling other factors.

Table 2: Impact of work experience, company size, and city on salary.

	Coefficient	Standard Error	T Stat	P-value	Lower 95%	Upper 95%	Lower Limit 95%	Up to 95%
Intercept	12.4059	0.4005	30.97604	6.2E-174	11..62048	13.19132	11.62048	13.19132
Years	1.562391	0.089803	17.39804	1.88E-63	1.386279	1.738502	1.386279	1.738502
Scale	0.000567	5.45E-05	10.40437	9.31E-25	0.00046	0.000673	0.00046	0.000673
Shanghai	3.018713	0.464786	6.494848	1.03E-10	2.107226	3.9302	2.107226	3.9302
Nanjing	-1.59049	0.69021	-2.30435	0.0213	-2.94406	-0.23692	-2.94406	-0.23692
Chongqing	-4.36678	0.497151	-8.78362	3.21E-18	-5.34174	-3.39182	-5.34174	-3.39182
Hangzhou	-0.33507	0.485295	-0.69045	0.48999	-1.28678	0.616638	-1.28678	0.616638
Shenzhen	3.203834	0.495118	6.470842	1.21E-10	2.232861	4.174806	2.232861	4.174806
Guangzhou	-1.79345	0.559216	-3.20709	0.001361	-2.89013	-0.69678	-2.89013	-0.69678

The city effect is also quite significant. Taking Beijing as the benchmark, Shenzhen (coefficient = 3.0833, $p < 0.001$) and Shanghai (coefficient = 3.0181, $p < 0.001$) are significantly higher than

Beijing, indicating that the salary premium of first-tier cities is still significant after controlling other variables; while the coefficients of Nanjing, Chongqing, Chengdu and other places are all negative and $p < 0.05$, showing their salary disadvantages compared with Beijing, further highlighting the impact of regional development imbalance on salary levels.

From the perspective of the overall regression model, the p-values of each variable are generally significant, indicating that education, experience, scale, and city all play an important role in explaining salary changes. Among them, work experience and city effects contribute the most, while education and company scale have relatively weak effects after controlling other factors, showing the salary structure characteristics of "strong experience, strong region, weak education, and small scale".

Table 3. Impact of work experience, company size, and education on salary

	Coefficient	Standard Error	T Stat	P-value	Lower 95%	Upper 95%	Lower Limit 95%	Up to 95%
Intercept	12.67714	0.340618	37.21805	1.6E-233	12.00916	13.34512	12.00916	13.34512
Years	1.565106	0.095349	16.41446	4.46E-57	1.378118	1.752094	1.378118	1.752094
Scale	0.000607	5.71E-05	10.62638	9.92E-26	0.000495	0.000719	0.000495	0.000719
Junior	-3.18256	0.489342	-6.50375	9.75E-11	-4.1422	-2.22291	-4.4122	-2.22291
Master	2.93691	0.872881	3.364618	0.00078	1.225113	4.648706	1.225113	4.648706
No requirement	-1.23915	1.180281	-1.04988	0.293895	-3.55378	1.075487	-3.55378	1.075487

Table 4: Baseline model with work experience and company size

	Coefficient	Standard Error	T Stat	P-value	Lower 95%	Upper 95%	Lower Limit 95%	Up to 95%
Intercept	12.19249	0.322377	37.82058	1.7E-239	11.56028	12.8247	11.56028	12.8247
Years	1.605849	0.095239	16.86131	6.02E-60	1.419078	1.792621	1.419078	1.792621
Scale	0.000654	5.74E-05	11.3798	3.66E-29	0.000541	0.000766	0.000541	0.000766

5 CONCLUSIONS

In the context of the ever-changing development of the digital economy, the position of product manager plays the role of a bridge connecting user needs, technology implementation, and business strategy, and becomes an important engine for enterprises to promote product innovation and respond to the market quickly. This paper takes the product manager position as the research object, based on the large-scale recruitment data of BOSS Direct Recruitment Platform, builds a regression framework that centers on four critical variables: city, education, work experience, and company size, and systematically explores the influence path and interaction mechanism of these variables on the salary level.

The results of the study show that city and work experience are the most significant factors affecting salary differences, with 3–5 years of experience often marking a distinct inflection point in career progression; academic qualifications still have structural value, and those holding at least a bachelor's degree tend to enjoy a notable wage premium in the market; and company size is reflected as a systematic advantage of the salary system and career stability. In large companies in Tier 1 cities, job seekers with a mid-to-high level of education and key experience thresholds are more likely to have significant salary returns and career advancement opportunities. These findings not only highlight the layered nature of the digital labor market, but also reflect the deep game of human

capital, regional resources and organisational systems behind the pay structure.

Further, the study not only provides quantitative evidence, but also responds to the structural problems of 'mismatch' and 'information asymmetry' in the real market. When job seekers face the dilemmas of skill prioritisation and ambiguous job descriptions, it is often difficult for them to precisely interpret what employers are truly seeking; while enterprises may also miss out on highly matching talents due to unclear job definitions and irrationally set experience thresholds. Through quantitative analysis of recruitment data, this paper constructs a coherent reasoning path linking market expectations to salary outcomes, which provides practical support for improving the accuracy of job seekers' career planning and the efficiency of corporate recruitment.

In terms of methodology, this paper integrates web crawlers, natural language processing, and statistical modelling techniques, effectively translates a large corpus of unstructured recruitment text into measurable analytical features. This technical path not only breaks through the dependence of traditional job analysis on questionnaires, interviews, and other methods, but also holds strong potential for adaptation across roles and platforms. In the future, if combined with in-depth semantic mining, industry classification models or time series modelling, it is expected to further portray the trend of skills evolution and dynamic changes in job demand, thus realizing data-driven career ecology research in the true sense.

From a broader perspective, the structural laws revealed in this paper are not only applicable to product manager positions but also provide theoretical references for understanding the value composition of high-knowledge and high-technology-intensive occupations in the context of the new era. In today's world, where companies are constantly pursuing agile innovation and high-quality growth, job pricing is no longer just a linear function of experience and education, but a synergistic game between corporate strategic goals, organisational structure, and talent ecosystem. Salary is often a reflection of the organisational expectations of a position and its criticality in the value chain.

Therefore, the significance of this paper is that it not only responds to the individual's confusion about the reality of career development paths but also provides a basis for organisations to optimise the allocation of human resources and build a scientific and reasonable job system. More importantly, it shows how human resource management and career planning can achieve more efficient docking and synergy under the data-driven logic, and promote the employment market from 'empirical judgement' to 'intelligent matching', to better serve the dynamic adaptation of people and jobs in the digital society. The dynamic matching between people and jobs in the digital society will be better served.

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