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Exploring the Impact of COVID-19 on Job Satisfaction Trends: A Text Mining Analysis of Employee Reviews Using the DMR Topic Model

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Abstract: Job satisfaction is a critical determinant in talent acquisition and corporate value enhancement. The COVID-19 pandemic has triggered a significant increase in online-based non-face-to-face services and consumption, leading to sustained growth in ICT industry job demand. Given the ICT sector's heavy reliance on human capital and its growing workforce demands, understanding the evolving factors of job satisfaction in this sector has become increasingly crucial. This study analyzed job satisfaction factors derived from employee reviews on an online job review platform using the Dirichlet Multinomial Regression (DMR) topic model, examining temporal changes in these factors before and after the COVID-19 pandemic. As a result, 25 distinct job satisfaction-related topics were identified, and their temporal distribution patterns were categorized into three trajectories: ascending, descending, and stable. Topics exhibiting ascending patterns included work–life balance, organizational systems, corporate culture, employee benefits, work environment, and software development practices. Conversely, factors demonstrating descending patterns encompassed annual compensation, task characteristics, supervisory relationships, employee treatment, commuting conditions, work-related stress, and welfare programs. The remaining topics maintained relatively stable patterns throughout the observation period. These findings contribute to both academic literature and industry practice by elucidating the evolutionary trends in job satisfaction determinants during the COVID-19 pandemic, thereby facilitating more informed strategic human resource management decisions in the ICT sector.

Keywords: COVID-19 pandemic; DMR topic model; employee reviews; job satisfaction; text mining

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1. Introduction

The COVID-19 pandemic has precipitated significant changes across the global economic, social, and cultural landscapes, with profound implications for work environments. In Europe, for instance, the share of remote workers surged from 5.4% in 2019 to 14% in [1]. Similarly, in the United States, the proportion of employees working from home five days a week increased from 17% to 44% [2]. In particular, Gallup's 2023 survey showed that more than half of American workers continued to work remotely over the past three years [3,4], and foresaw hybrid work models—combining traditional workplace and working remotely—as the emerging standard. This evidence underscores that the pandemic's impact on work practices is structural and enduring rather than merely a temporary adjustment. This rapid transition from traditional, office-centered work models to remote and hybrid models has not only altered organizational operations but also fundamentally transformed how employees perform their tasks.

Concurrent with these changes, the acceleration of digital transformation triggered by the pandemic has brought about significant shifts in the nature of work. Digital transformation goes beyond merely altering work formats; it has redefined job characteristics in ways that influence both job satisfaction and organizational commitment [5]. Furthermore, the accelerated digital transformation has led to an increased importance of the ICT sector, as evidenced by the growth in ICT capital investment in OECD countries. This investment increased from an annual growth rate of 0.5% between 2010 and 2019 to 1.8% between 2019 and 2020 [6]. The digital sector, encompassing ICT, experienced a downturn due to global value chain disruptions. However, the demand for digital infrastructure has exhibited a substantial surge, driven by the proliferation of remote work and non-face-to-face services [7]. In Korea, the ICT industry's non-face-to-face and non-contact technology-related sectors have rapidly expanded [8]. A recent study examined the role of ICT in the economic resilience of countries during the pandemic, finding that countries with a high ICT intensity showed lower output losses in terms of cyclical GDP [8].

As the ICT sector's importance continues to grow, it is being integrated into various industrial sectors through rapid technological development and innovation. Consequently, the working environment and job satisfaction in these industries are becoming increasingly significant. Given the nature of the ICT industry, which demands technology-oriented work and adaptation to rapid change, the psychological stability and job satisfaction of employees are identified as critical factors directly associated with the competitiveness and sustainability of the company.

This study aims to analyze the impact of COVID-19-induced changes in work environments on the job satisfaction of employees within the ICT sector. Job satisfaction, which reflects individuals' positive or negative attitudes toward their jobs, has long been regarded as an important factor influencing not only personal well-being but also corporate growth, economic development, and productivity [9].

The majority of extant empirical studies on job satisfaction have relied on survey data [10,11]. However, survey-based approaches may have the following limitations. First, respondents may not always express their opinions candidly, which introduces a degree of bias [12]. Second, these approaches are limited to collecting information on predefined topics, which can limit the depth and breadth of the insights gathered [13]. Finally, survey research often suffers from insufficient sample sizes, which can compromise the reliability and generalizability of the results [14]. With the widespread adoption of smartphones and the provision of services online, similar to how consumers now refer to others' opinions online before making decisions, such as purchasing products or reserving restaurants, job seekers have been observed to consult online platforms like Glassdoor when making employment decisions [15]. Platforms such as Glassdoor and Indeed facilitate active online information sharing, and because the data are generated anonymously, issues related to social desirability bias are minimized [16], and the utilization of text mining methods such as topic models has been demonstrated to facilitate more precise measurement of job satisfaction [12,13,17].

Therefore, this study utilizes review data from Jobplanet, a Korean service similar to Glassdoor that aggregates authentic opinions on corporate culture and work environments based on the actual experiences of employees. The analysis is conducted using the Dirichlet-Multinomial Regression (DMR) Topic Model. DMR topic modeling improves upon Latent Dirichlet Allocation (LDA) by incorporating document-level metadata, enhancing topic distribution accuracy and interpretability [18]. Compared to Structural Topic Models (STM), DMR is computationally more efficient while still leveraging metadata to improve robustness, especially in sparse data settings [19,20]. DMR topic modeling is particularly suited for analyzing how document characteristics affect topic distribution patterns, thereby enabling temporal analysis of job satisfaction factors throughout the pandemic period.

This study is organized as follows. In Section 2, the research methodology is presented, with detailed descriptions of the data collection and analytical techniques employed in this study. Section 3 outlines the results obtained from the analysis, while Section 4 offers a comprehensive discussion of these findings. Finally, Section 5 concludes the paper by summarizing the key insights, addressing the study's limitations, and suggesting directions for future research.

2. Research Methodology

This study is anchored in a pragmatic research philosophy, employing a predominantly quantitative approach (topic modeling) with a qualitative interpretive step in the topic definition. The analytical framework of this study consists of five phases, as illustrated in Figure 1: (1) data collection, (2) data preprocessing, (3) topic coherence assessment, (4) topic modeling with temporal distribution analysis, and (5) results interpretation. Data were collected from Jobplanet, a Korean online platform where employees share company reviews. The study analyzed reviews spanning from May 2019 to August 2020 to examine topic variations in response to the COVID-19 pandemic. The preprocessing phase involved extracting nouns, including compound nouns and neologisms, from the textual review data and the specific data processing method will be explained in more detail later. DMR Topic Model was employed using the tomotopy library in Python 3.9.0 to identify and define job satisfaction-related topics and analyze their temporal distribution patterns. The topic modeling analysis yielded twenty-five distinct job satisfaction-related topics, revealing temporal trends specific to the ICT industry. All graphs were generated with matplotlib.

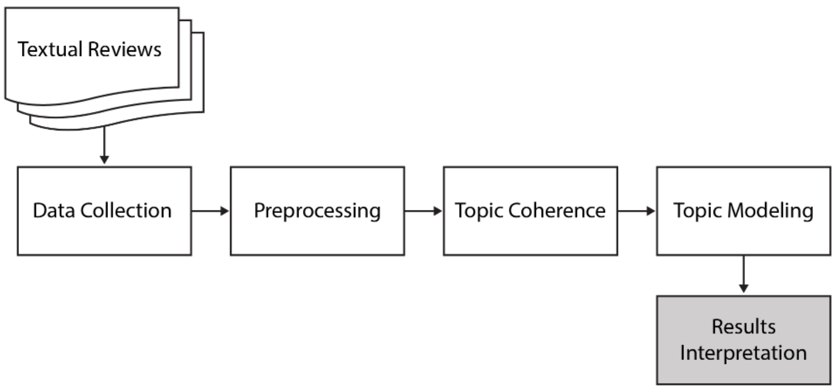

Figure 1. Research Framework. Source: Author's own work.

2.1. Data Collection

Jobplanet is a job recruitment advertisement and company evaluation-sharing platform that provides information on 95% of companies in Korea employing five or more people. It effectively serves as the Korean equivalent of Glassdoor. The platform has enhanced its review management policies by incorporating the ISO standard on online consumer reviews (ISO20488:2018) [21]. Reviews on Jobplanet are based on users' actual work experiences and are structured into four sections: a company summary review, the company's strengths, the company's weaknesses, and a message to the management. This format offers detailed insights into the specific attributes that contribute to a company's appeal.

As of February 2025, Jobplanet hosts review information for 90,393 companies. Within its ten industrial categories—service industry, manufacturing/chemicals, healthcare/pharmaceuticals/welfare, distribution/trade/transportation, education, construction, IT/web/telecommunications, media/design, banking/finance, and public institutions/associations—the IT/web/telecommunications sector comprises 12,675 companies.

The data collection process encompassed text reviews across four distinct categories: titles, advantages, disadvantages, and management suggestions, as illustrated in Figure 2. Each review entry included employee metadata (employment status, posting date, job role) and organizational information (company name, industry classification). In this study, companies with at least five reviews were selected for analysis to prevent bias caused by data scarcity. Of all the reviews on Jobplanet, only those classified under ICT were collected, resulting in an initial dataset of 52,561 reviews spanning May 2019 to August 2020. This enabled analysis of topic evolution throughout the COVID-19 pandemic period. The ICT companies on Jobplanet cover various sectors such as Portal/Internet/Content, E-Commerce, Network/Telecommunications, Hardware, IT Consulting, and Gaming. However, it is important to note that the ICT companies have reviews on Jobplanet.

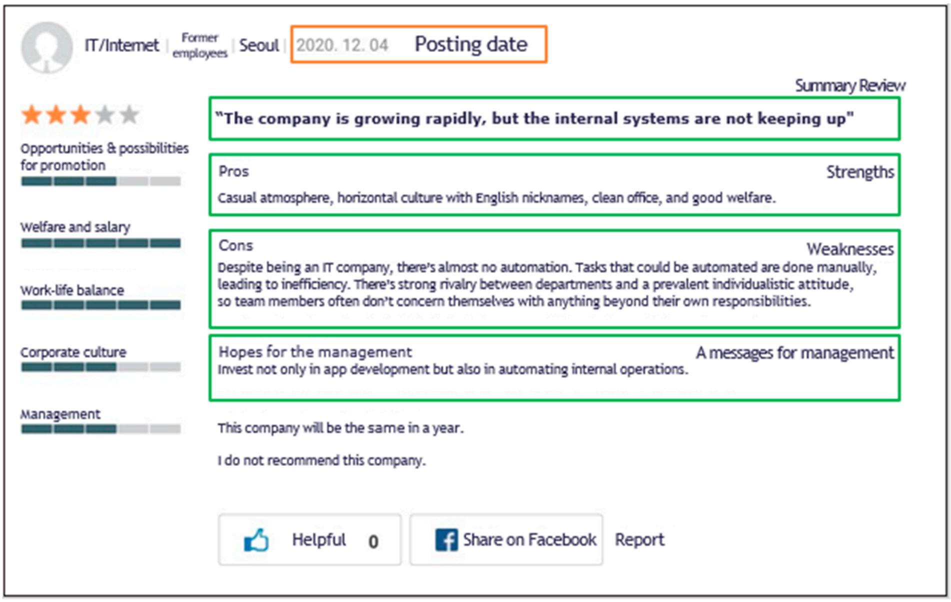

Figure 2. Example of collected review.

This study aims to find out how COVID-19 affects job satisfaction trends. When measuring the effects of COVID-19, using data from a long period of time after the outbreak of COVID-19 has the advantage of utilizing more data, but data from a long period of time after the outbreak of COVID-19 has the disadvantage that the effects of COVID-19 may be weakened. For this reason, [22] used data from before (June and September 2018) and after (June 2020) to assess the effects of pandemic risk on cooperation and social norms, and [23] used data between June 2019 and June 2021 to explore potential factors which influence guests' hotel recommendations before hotels were shut down due to COVID-19 and after they reopened.

In this study, in order to select a period during which the effects of COVID-19 could be significant, the analysis period was set to be from November 2019 to February 2020, when COVID-19 is believed to have occurred, and the 6 months before and after. Consequently, the final dataset comprised 29,864 reviews from 868 companies, each having five or more employee reviews (Table 1).

Table 1. Number of Reviews Before and After Filtering.

Date	Before Filtering		After Filtering	
	Number of Reviews	Ratio (%)	Number of Reviews	Ratio (%)
May 2019	3655	6.95	2184	7.31
Jun 2019	3234	6.15	1893	6.34
Jul 2019	3617	6.88	2100	7.03
Aug 2019	3266	6.21	1885	6.31
Sep 2019	2971	5.65	1786	5.98
Oct 2019	2979	5.67	1777	5.95
Nov 2019	3140	5.97	1775	5.94
Dec 2019	3175	6.04	1758	5.89
Jan 2020	3929	7.48	2088	6.99
Feb 2020	3610	6.87	1915	6.41
Mar 2020	3225	6.14	1775	5.94
Apr 2020	2807	5.34	1558	5.22
May 2020	2818	5.36	1575	5.27
Jun 2020	3158	6.01	1752	5.87
Jul 2020	3610	6.87	2079	6.96
Aug 2020	3367	6.41	1964	6.58
Total	52,561	100	29,864	100

The temporal distribution of the filtered review corpus is visualized in Figure 3.

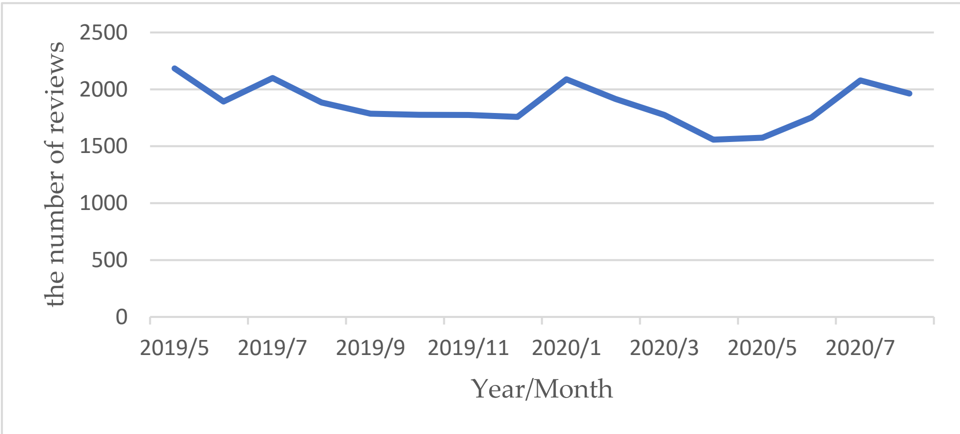

Figure 3. Number of reviews after filtering.

2.2. Data Preprocessing

Given the unstructured nature of employee reviews, preprocessing was conducted to optimize analysis efficiency and accuracy. The preprocessing sequence consisted of three main steps: tokenization for noun extraction, bi-gram and tri-gram extraction, and stopword removal. Morpheme analysis was performed on the collected text data. Despite the importance of sentimental analysis, this study utilized only nouns for DMR topic modeling, as nouns serve as primary semantic indicators in natural language processing applications, including information retrieval, document classification, text summarization, and information extraction [24].

This approach required Part-Of-Speech (POS) tagging, which was implemented using the KoNLPy library with the MeCab-ko package in Python. MeCab [25], an open-source morphological analyzer based on Conditional Random Fields (CRF), was originally developed for Japanese language processing but has been adapted for broader applications. MeCab-Ko, the Korean extension of MeCab, leverages the morphological and syntactic similarities between Japanese and Korean. Since its introduction in 2013, it has been extensively employed in Korean Natural Language Processing (NLP) tasks due to its high accuracy and usability [26]. Compound nouns and neologisms were extracted using the NLTK package's N-gram collocation feature. N-gram represents a sequence of n consecutive tokens (in this study, syllables), where a token is defined as a syllable unit within a sentence. Table 2 illustrates N-gram decomposition using the example sentence, "This is not a pipe".

Table 2. Examples of N-gram.

N-Gram	Examples
Uni-grams	This, is, not, a, pipe
Bi-grams	This is, is not, not a, a pipe
Tri-grams	This is not, is not a, not a pipe

To extract meaningful topics and reduce the number of words processed during preprocessing, special characters, numbers, English words, and emoticons were excluded from the analysis, and stopwords were removed. As a result, a total of 29,848 reviews containing 10,663 unique nouns were used for DMR topic modeling.

2.3. Topic Coherence

Topic modeling requires pre-specification of the number of topics. While perplexity scores have traditionally been used for this purpose, they primarily indicate model learning performance and present challenges in human interpretation [27]. Topic coherence, proposed by [28], addresses these limitations by measuring the semantic similarity of words within each topic. Higher coherence scores indicate that topics comprise more semantically related words, enhancing the interpretability of the topic modeling results. Using the Gensim library, this study calculated the CV coherence score to evaluate models with topic numbers ranging from 2 to 65. As illustrated in Figure 4, the optimal number of topics was determined to be 25, corresponding to the maximum coherence score.

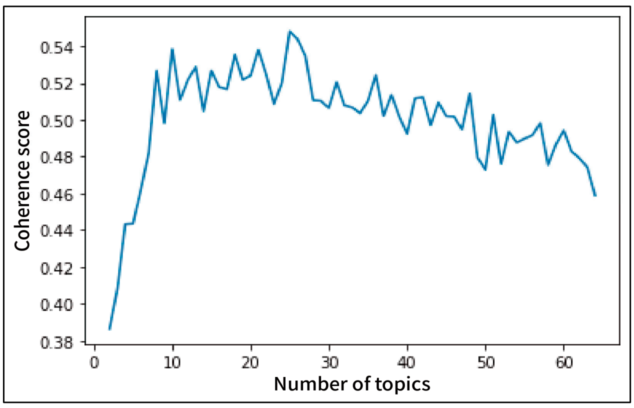

Figure 4. Result of topic coherence.

2.4. DMR (Dirichlet-Multinomial Regression) Topic Model

Topic modeling is a statistical technique used to discover latent topics within a collection of documents [29]. These algorithms are particularly effective for analyzing large-scale data and can be applied not only to textual data but also to various types of information, including genetic sequences, images, and social networks, to identify underlying patterns [30].

DMR is an extension of LDA (Latent Dirichlet Allocation) topic modeling that incorporates document metadata characteristics (such as author, journal name, and publication date) as a third parameter in analyzing document and topic distributions [18]. Unlike traditional LDA, DMR topic modeling allows the prior distribution (α) of topics to vary according to document-specific metadata characteristics [31]. This flexibility enables the topic distribution within documents to be influenced by metadata features such as publication date. The DMR topic model is particularly effective when analyzing how document characteristics affect topic distributions across different contexts. Due to these advantages, DMR topic modeling is being used in various recent studies [32–34].

As illustrated in Figure 5, the DMR model algorithm extends the LDA model by incorporating metadata (x) to derive topics based on specific attributes while maintaining the core functionality of deriving topic distributions within documents and word generation probabilities. In the DMR model, μ is the mean of λ (hyperparameter), σ^2 is the variance of the prior on parameter values, α is the prior distribution over topics, x is metadata, θ is topic proportions, z is a topic assignment for the nth word in document d, w is the nth word in document d, φ is the probability distribution over the vocabulary, and β is the Dirichlet prior on the topic-world distributions.

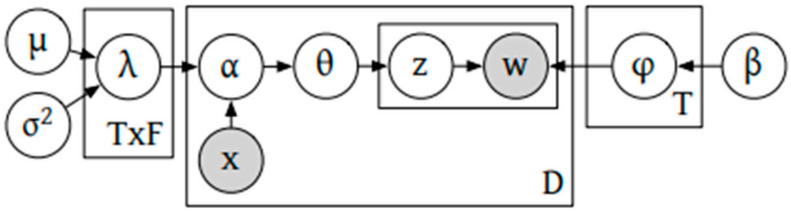

Figure 5. DMR model [18].

The model follows a structured process: (1) extracting metadata from documents, (2) adjusting topic distributions based on metadata values, and (3) assigning words to topics similarly to LDA but with metadata-conditioned topic weights. This results in a metadata-aware topic modeling approach, which is particularly effective for analyzing how document characteristics influence topic distributions across different contexts.

Sentiment analysis is another option to analyze user reviews. Sentiment analysis is a widely used technique for extracting emotional polarity from text, but it has several limitations. It often struggles with understanding context, handling ambiguity, and detecting sarcasm, leading to misclassification [35,36]. Moreover, sentiment analysis typically relies on predefined categories (positive, negative, neutral), making it difficult to capture nuanced or mixed emotions [37]. Additionally, it is highly domain-dependent, requiring customized models for different industries or applications [38]. In contrast, the DMR topic model provides a more sophisticated approach to text analysis by extracting meaningful topics from documents while incorporating metadata for deeper insights [18,39]. Unlike sentiment analysis, which primarily classifies emotions, DMR topic modeling identifies patterns across texts, allowing for contextual and thematic analysis. Furthermore, DMR is more effective for analyzing unstructured data, such as research papers or policy documents, where identifying sentiment may be less useful than discovering topic trends [40]. By leveraging quantitative modeling, DMR enables researchers to explore how topics evolve over time and across different contexts, making it a more robust tool for large-scale text analysis [41]. Given these advantages, DMR topic modeling is often a superior choice for comprehensive text analysis compared to sentiment analysis.

Therefore, the DMR model was applied to analyze Jobplanet reviews and their temporal topic trends. The analytical framework was structured as follows: the corpus comprised the collection of online reviews, individual reviews served as documents, job satisfaction factors were represented as topics and temporal information (monthly data) served as metadata.

3. Results

This section presents our findings by first detailing the prominent topics identified in the employee reviews, followed by an analysis of how these topics have shifted over the course of the COVID-19 pandemic.

3.1. Topic Analysis

Table 3 presents the 25 topics derived from the topic modeling analysis, along with the top 30 keywords associated with each topic. To facilitate interpretation, these 25 topics were further classified into nine higher-level categories. The keywords listed on the right side of the table represent the results obtained through topic modeling, while the topic names on the left were assigned by the researcher based on the type and frequency of the associated keywords. Since topic names were determined from the derived keywords, it is crucial to identify discriminative keywords that effectively characterize each topic. The keywords and topics resulting from the modeling process illustrate the key issues associated with job satisfaction in the ICT industry.

Table 3. Extracted job satisfaction factors by topic modeling.

	Main Category	Topic Number	Topic Name	Keyword
1	Leadership and management	1	CEO	CEO, Representative, Meeting, Mindset, Employee, Opinion, Resignation, Communication, Management, Executives, Team Leader, Director, Representative Director, Executive Officer, Old-fashioned (Conservative), Disregard, Practitioner, Contents, Department Head, Board members, Leaving Work, going to Work, Flattery, Senior, Report, Schedule, Snack, Division head, Middle manager, Head, Career
		5	Supervisor	Team Leader, Evaluation, Politics, Team member, Competence, Employee, Responsibility, Leader, Resignation, Upper management, Old-fashioned, Practical work, Job position, Practitioner, Executive Officer, CEO, Job title, Managerial level, Internal politics, Executives, Circle, Performance evaluation, Human resources, Department head, performance, Recognition, Promotion, Supervisor, Middle manager, Treatment
		9	Executives	Executives, Mindset, Resignation, Representative, Management, Responsibility, Executive, Practitioner, Board members, Future, Manager, Practical work, Interest, opinion, Job transition, Politics, Circumstance, Middle manager, Industry, help, communication, Struggle, Leader, Senior, IPO, Present, Owner, attitude, Reassignment, Coffee
		14	Internal politics	Old-fashioned, Supervisor, Politics, Resignation, Female, Employee, Senior, Salary, Read the atmosphere, Territorial behavior, Job position, Internal politics, Male, Team dinner, Drinking, Circle, leaving work on time, Able to leave work on time, Career, New employee, Gossip, Authoritarian culture, Lunchtime, School, Disregard, Superior, Subordinate, Corporate life, Promotion, Smoking Attitude
2	Work and life balance	18	Work and life balance	Annual salary, Welfare, Work–life balance, Job transition, Career, Annual salary increase, Workload, Same industry, New employee, Industry, Career, Desire, Treatment, compensation package, team by team, Old-fashioned, Effort, Work environment, System, Entry-level salary, Bonus, Incentive, Pressure to use annual leave, Stability, Department by department, Able to leave work on time, Salary table, Overtime work
3	Organizational culture and atmosphere	8	Atmosphere	Atmosphere, Flexibility, Welfare, Annual leave, Horizontal, Culture, Environment, Read the atmosphere, Commuting, System, Communication, Using annual leave, Overtime work, Work environment, Vertical, Pressure to use annual leave, Vacation, Intervention, Autonomy, Team dinner, Respect, Available, Stress, Opinion, Adaptation, Leaving work, Job position, Position, Effort, Team member, Age group
		12	Culture	Development, Culture, Opportunity, Effort, Atmosphere, Performance, Organization, Member, Compensation, Colleague, Assessment, Environment, Passion, Executives, System, Decision making, Leader, Vision, Competence, Communication, Change, Autonomy, Talent, Responsibility, Organizational culture, Horizontal, Objective, Sharing, Collaboration, Will, System
		20	Cultural system	Culture, Compensation, Old-fashioned, Vertical, Military culture, Team dinner, Authoritarian culture, Internal politics, Change, Executive, Circle, Vertical culture, Effort, Report, Military style culture, Military, Organization, Organizational culture, Military-style, Horizontal culture, Drinking, Seoul, Image, Adaptation, Innovation, Hierarchical obedience, Vertical organizational culture, Overtime work, Building, Outdated, Pride

Table 3. *Cont.*

	Main Category	Topic Number	Topic Name	Keyword
4	Job characteristics and workload	4	Task	Task, Schedule, Meeting, Portfolio, Sharing, Process, Project progress, Document, Program, Test, Data, Outcome, Approach, Plat, Quality, Practitioner, Report, Brand, Help. Process, Environment, Coordination, Maintenance, Image, Report, Operator, Analysis, Feedback, Material, Explanation, Function
		11	Work stress	Performance, Stress, Revenue, Performance pressure, Incentive, Salary, Pay, Base salary, Assessment, Employee, New employee, Manager, Burden, Team leader, Consultation, Structure, Competition, Sales pressure, Adaptation, Internet, Mental State, Senior, Field, Contract, Promotion, Knowledge, Event, Superior, Job, Incentive system
		19	Work system	System, Process, Operation, Welfare, Scale, Overtime work, Unsystematic, Human resources, Career, Job position, Employee, Handover, Allocation, Procedure, Management, Human resource management, Fundamental, Adaptation, Practical work, Recruitment, Help, Medium-sized company, Workload, Composition, format, Regulation, Procedure, Use of annual leave, Approach, Plan
		23	Software development	Developer, Technology, Competence, Product, Environment, Treatment, Study, New employee, Job category, Developer treatment, Technical expertise, Timeline, Maintenance, Development, Investment, Interest, Site, Research, Opportunity, Business, Process, Effort, Software, New, Knowledge, Development job field, Background, Technology development, Function, Awareness
5	Workplace environment	2	Workplace environment	Going to work, Building, Restroom, Lunch break, COVID-19, meeting, Space, Journalist, Article, Team dinner, Chair, Lunch, Being late, Remote work, Notice, Refrigerator, Cleaning, Workshop, Desk, Air conditioner, Summer, Laptop, Partition, Meeting room, Snack, Coffee machine, Elevator, Mask, Computer, Office relocation, Supplies
		7	Employment types	Temporary employee, Intern, Full-time employee, Dispatch employee, Conversion to full-time employment, Recruitment, Opportunity, Treatment, Transition, Contract, Discrimination, Read the atmosphere, At the time, Employment, Temporary worker, Facility, Open recruitment, Leaving work on time, Practical work, Able to leave work on time, Supervisor, Interview, Transition from contract to full-time employment, Dispatched contract worker, Welfare, Building, Full-time recruitment, Weight, Duty
		10	Commuting, overtime work	Overtime work, Leaving work, Monthly salary, Going to work, Overtime allowance, Read the atmosphere, Allowance, Annual leave, Team dinner, Weekend, Employee, Resignation, Leaving work on time, Weekend work, Vacation, Meeting, New employee, Lunch, Working on weekends, Stress, Full capacity, Dinner, Lunch break, Timeline, Event, Holiday, Out-of-office work, President, Task, Workload
		22	Workplace location and environment	Welfare, Location, Building, Commuting, Facilities, In-house cafe, Lunch, Overtime work, In-house cafeteria, Meal, Cafeteria, Going to work, Lunch break, Seoul (The capital of South Korea), Surroundings, Coffee, Complimentary, Team by Team, Pangyo (A place where many ICT-related companies are located in South Korea), Gym, Developer, Convenience, Snack, Area, Nearby, Commuter bus, Discount, Shuttle bus, Golf
		24	Business trip and dispatch	Business trip, China, Abroad, Foreigner, Seoul, Province, English, Executive, Headcount, Dispatch, Business trip allowance, Area, Developer, Japan, Opportunity, United States, Site, Overseas business trip, Salary, Busan, On-site, Korean, Regional business trip, Chinese, Youth, Situation, Recruitment, Response, Korean branch, Life
6	Company policies	0	Vacation and annual leave	Welfare, Overtime work, Annual leave, Read the atmosphere, Flexibility, Annual salary, System, Regulation, Vacation, Salary, Leaving work, Available, Use of annual leave, Pressure to use annual leave, Leaving work on time, Treatment, Workload, Environment, Promotion, Career, Developer treatment, Able to leave work on time, Investment, Career, Workload, Promotion opportunity, Senior pressure regarding annual leave, Comparative freedom, Superior, Commuting time
7	Compensation	3	Annual salary	Annual salary, New employee, Job position, Resignation, Monthly salary, Job transition, Assessment, Career, Promotion, Salary increase, Salary negotiation, Employee, Team leader, Structure, Experienced hire, Annual leave, Department manager, Entry-level salary, Superior, Years of experience, Assistant manager, Treatment, Inverted pyramid structure, Competence, Increase, Meaning, Headcount
		13	Welfare	Welfare, Salary, Stability, Workplace environment, Effort, Headcount, System, Treatment, Atmosphere, Size, Regulation, Environment, Promotion, Benefits, Welfare benefits, Compensation, Policy, workload, Performance, Job position, Work–life balance, Employee welfare, Wages, Promotion opportunity, Building, Female, Terms, Incentive, Image
		21	Benefits	Welfare, Vacation, Welfare points, System, Full capacity, Annual leave, Card, Incentive, Event, Points, Organizational restructuring, Policy, Politics, Benefits, Team by Team, In-house café, Cost, Read the atmosphere, Birthday, Gift, Discount, Pressure to use annual leave, Medical check-up, Travel, Cash, In-house cafeteria, Purchase, Coupon, Subsidy, Quarter
8	Business and management	15	Business	Business, Stability, Growth, Investment, Operation, Future, Revenue, Culture, Change, Structure, Executives, Organization, Industry, Market, Size, Remuneration, Technology, Opportunity, System, Vision, Situation, Challenge, Work–life balance, Present, Profit, Effort, Developer, Environment, New, New business, Management
		17	Management and operation	Executives, Board member, Business, Operation, President, Management, System, Resignation, Politics, Welfare, Mindset, Organization, Owner, Headcount, Size, Chairman, Promotion, Human resources, Vision, Business division, Monthly salary, Core, Performance, Organizational restructuring, Circle, Future, Interest, CEO, Salary, At the time

Table 3. *Cont.*

	Main Category	Topic Number	Topic Name	Keyword
9	Unclassified	6	Miscellaneous	Resignation, Monthly salary, Representative, Executives, President, Mindset, Interview, Recruitment, Responsibility, Operation, Consumables, Revenue, Salary, Lie, Building, Surroundings, Team leader, Director, Explanation, Management, New employee, Retirement allowance, Personality, Disregard, Wages, Mistake, Recommended resignation, During the interview, Rating
		16	Careers	New employee, Dispatch, Career, Annual salary, Experienced hire, Developer, Job transition, Resignation, Headcount, Interest, Years of experience, Site, Adaption, Operation, Experienced worker, Workplace, Employee, Competence, Treatment, Dispatch site, Sense of belonging, Monthly salary, Recruitment, New employee, Salary negotiation, Dispatch employee, Opportunity, Senior, Project assignment, Mentor, Task

The topics extracted from topic modeling were classified into nine main categories; the details of each category are presented in Table 3 below.

3.2. Topic Trends Analysis

The temporal analysis of topic distributions, derived from DMR topic modeling with monthly metadata, revealed distinct patterns in job satisfaction factors. Figure 6 depicts the probability distributions of all 25 topics over time, with a vertical dotted line indicating the onset of the COVID-19 pandemic.

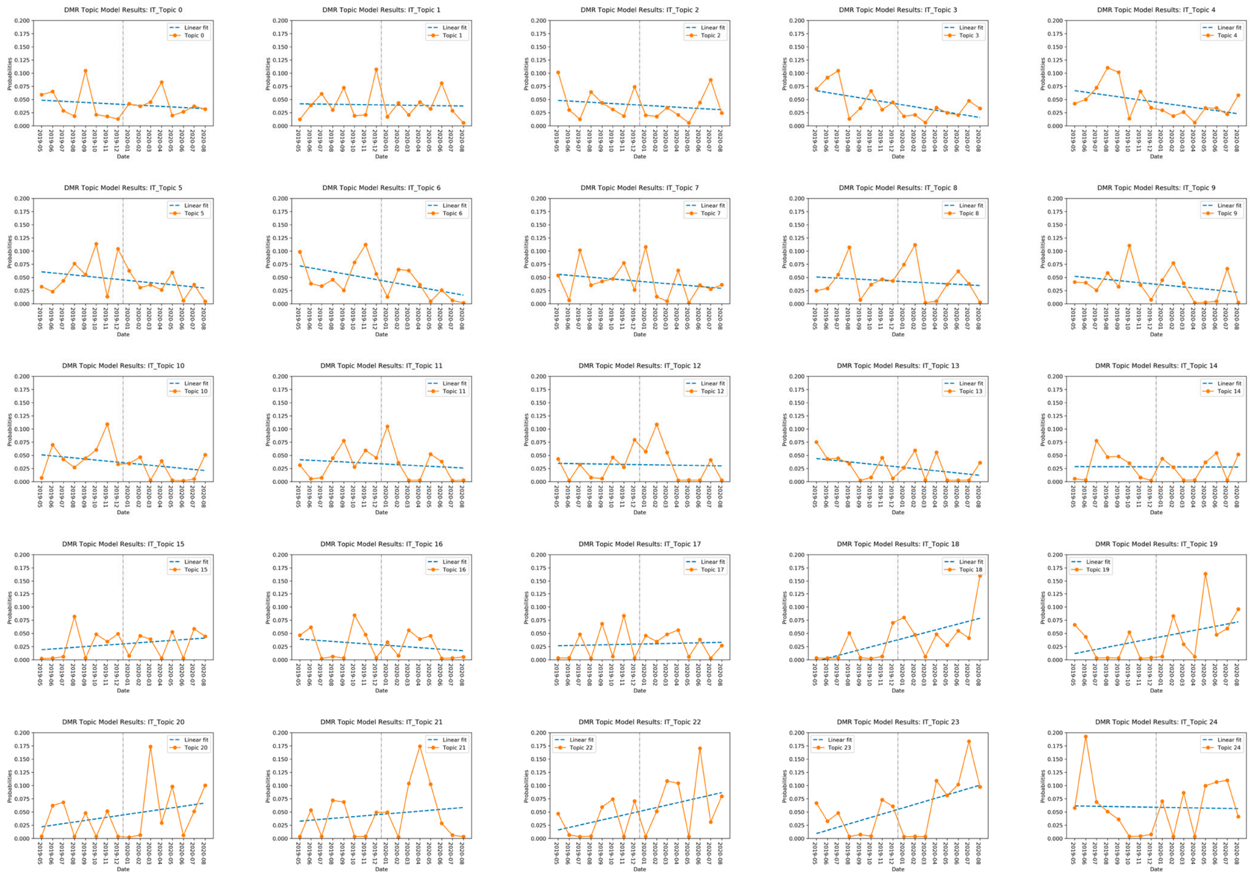

Figure 6. Results of DMR topic modeling.

Based on linear trend analysis, the topics were classified into three categories: ascending, descending, and stable patterns.

- Ascending Patterns (Topics 18–23): Topics exhibiting increasing probability distributions post-COVID-19 included work–life balance (Topic 18), work systems (Topic 19), organizational culture (Topic 20), employee benefits (Topic 21), workplace environment

(Topic 22), and software development (Topic 23). Work–life balance demonstrated notable volatility, with a sharp increase in August following a temporary decline in March 2020. Working system-related discourse showed overall upward momentum despite periodic fluctuations. Cultural topics displayed an increased amplitude of variation post-pandemic. Benefit-related discussions peaked in April 2020 after maintaining stability pre-COVID-19. Workplace environment topics showed amplified fluctuations with an overall positive trend from January 2020. Software development-related discourse exhibited consistent growth from March 2020. Working conditions, identified as a critical factor in job satisfaction in the ICT industry [18], include factors such as ventilation, lighting, tools, workspace, and facilities [19,20]. Topics such as work–life balance (Topic 18), working system (Topic 19), Organizational Culture (Topic 20), Employee benefits (Topic 21), and workplace environment and location (Topic 22) are directly associated with working conditions.

- Descending Patterns (Topics 3–6, 10, 11, 13): Topics showing declining trends post-COVID-19 included annual salary (Topic 3), task characteristics (Topic 4), supervisors (Topic 5), miscellaneous (Topic 6), commuting and overtime (Topic 10), work-related stress (Topic 11), and welfare (Topic 13). Notably, work stress peaked in January 2020 before showing an overall decline.
- Stable Patterns: The remaining topics generally maintained consistent distributions, with some exceptions. Topic 24 (workplace location and environment) exhibited a unique pattern: despite an overall flat linear trend, it showed decline after June 2019, followed by an increasing trend from January 2020 post-COVID-19.

4. Discussion

The results of this study indicate noticeable shifts in topic salience within employee reviews, particularly around the onset of the COVID-19 pandemic. While the observed trends highlight changes in how employees discuss various aspects of their work experience, they do not conclusively demonstrate the direct effects on job satisfaction. Instead, they may suggest evolving priorities, potentially influenced by global shifts toward remote or hybrid work, digital transformation, and increased recognition of the importance of healthy work environments.

Firstly, the ascending trends observed in work–life balance (Topic 18), work systems (Topic 19), organizational culture (Topic 20), employee benefits (Topic 21), and workplace environment (Topic 22) could suggest that extrinsic factors gained prominence during the pandemic period. Although it remains uncertain whether these increases translate into enhanced job satisfaction, they may signal heightened awareness or discourse around flexible work arrangements and supportive work conditions. This pattern aligns with [42] reported that "work environment" and "work–life" categories were prevalent among large-scale review data, indicating that compensation is not necessarily the sole determinant of employee decisions. Similarly, according to the "Connecting with the Workforce" report by Kantar, a data consulting firm, a majority of remote or hybrid workers expressed satisfaction with their arrangements due to improved work–life balance and reduced commuting burdens [43]. However, further empirical analysis (e.g., turnover rates or direct measures of satisfaction) would help verify whether employees genuinely perceive these factors as more influential than before.

Secondly, the declining attention to annual salary (Topic 3), task characteristics (Topic 4), supervisors (Topic 5), commuting and overtime (Topic 10), and work-related stress (Topic 11) may reflect a reduced focus on traditional drivers of job satisfaction and managerial oversight. It is possible that employees' immediate concerns shifted toward flexibility, remote collaboration, and psychological well-being, especially amid the uncertainties of the pandemic. The authors of [44] noted that "working conditions", opportunities for personal autonomy, and collegial harmony emerged as leading factors affecting employee attitudes during COVID-19. Nevertheless, the observed decrease in these topics does not confirm that pay or managerial factors have lost their effectiveness entirely; rather, employees might be balancing these aspects against newly emerging priorities.

Thirdly, the emphasis on organizational culture (Topic 20) might indicate the growing relevance of cultural alignment and internal communication in remote or hybrid contexts. One study [45] similarly underscored the significance of organizational culture for remote work satisfaction, including transparent communication and shared values. While a rise in culture-related discourse could hint at employees' increased attention to cultural aspects, additional investigation—such as correlation with employee engagement metrics—would be required to conclude that these topics directly improve satisfaction.

Fourthly, the upward trend in software development (Topic 23) may suggest that development tasks, technical capabilities, and knowledge have taken on greater importance within the ICT sector. As digital transformation accelerates, it appears that discourse around development processes, tools, and professional skill sets has increased. Although these patterns do not necessarily prove that software development aspects directly boost job satisfaction, they indicate that organizations and employees themselves could be placing greater emphasis on technical expertise and innovation in response to rapidly changing market and workplace conditions.

The findings of this study, derived from an analysis of job satisfaction factors within ICT companies, may not be generalizable across all industries. However, according to [46], although financial rewards remain important, employees across diverse industries are increasingly prioritizing factors such as flexibility, work–life balance, and meaningful work, suggesting that this shift is not confined to a single sector. Concurrently, the authors of [47] observed comparable distributions of job satisfaction factors across diverse industries, suggesting minimal differences among them. Furthermore, the authors of [48] found that factors positively influencing job satisfaction were broadly consistent across nine industry sectors. Consequently, changes in job satisfaction determinants resulting from shifts in working environments and technological advancements are more likely to represent broader labor-market phenomena than industry-specific trends.

5. Conclusions

This study examined the impact of COVID-19-induced changes in work environments on job satisfaction in the ICT sector by analyzing review data from Jobplanet using the DMR topic model. According to [49], the risk of pandemics has been continuously increasing, and as mentioned by [50,51], the outbreak of viruses with global impacts, such as COVID-19, is expected to occur more frequently than before. Therefore, the results of this study are expected to provide important implications when a pandemic occurs again in the future.

The findings indicate a marked shift in employee discourse during the pandemic, with increased attention to extrinsic job factors such as work–life balance, organizational culture, and employee benefits, and a relative decline in discussion surrounding salary and managerial oversight. While these observations suggest evolving employee concerns and priorities in response to remote work and digital transformation, it remains unclear whether these thematic changes have a positive or negative effect on job satisfaction. Although this study mentioned the shortcomings of sentiment analysis, sentiment analysis and DMR could be complementary rather than mutually exclusive. In accordance, future investigations could address this gap by incorporating methods such as sentiment analysis or direct measures of employee attitudes. Furthermore, because the analysis focused on a relatively short time frame of 16 periods, there was insufficient scope to determine the statistical significance of the observed shifts. Extending the dataset to cover a longer period would allow for a more robust assessment (e.g., machine learning for predictive insights such as Recurrent Neural Networks and Prophet) of the sustained influence of these evolving factors on job satisfaction.

Although the impact of COVID-19 may vary by industry, our study exclusively focuses on the ICT sector. Therefore, we believe that future studies targeting a broader range of industries could provide richer insights through comparative analysis across industries. Taken together, however, these results highlight how organizations must adapt to emerging employee preferences regarding flexibility, culture, and benefits, particularly as digital transformation continues to reshape the modern workplace.

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