Generative AI, Job Satisfaction and Type of Work

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Abstract

This study examines how generative artificial intelligence (generative AI) relates to job satisfaction among employees in the financial services sector, considering differences across types of work and exposure to AI-driven task transformation. Drawing on socio-technical systems theory, job satisfaction is conceptualized as an emergent outcome shaped by the alignment between technological change and organizational conditions. The analysis is based on a survey of 433 white-collar employees in Poland's financial services industry and employs ordered logit models. The findings show that job satisfaction is positively associated with organizational support for AI adoption and leadership effectiveness in managing AI-driven change, whereas individual enthusiasm toward generative AI is not positively related to satisfaction. Moreover, AI-related technostress is more strongly associated with lower job satisfaction in roles with higher exposure to AI-driven task transformation. Overall, the results highlight the contingent nature of generative AI's impact on job satisfaction and emphasize the importance of socio-technical alignment in AI-enabled work environments.

Keywords: generative AI tools; job satisfaction; human–AI interaction; technostress; organizational support; socio-technical systems

Introduction

Artificial intelligence (AI) is reshaping organizational work processes, offering unprecedented opportunities while introducing new managerial challenges. As human–machine collaboration becomes embedded in everyday operations, both employees and leaders must adapt to a work environment where human capabilities are increasingly interdependent with algorithmic systems. The effective integration and acceptance of AI technologies are therefore critical for organizational performance and sustained competitiveness.

AI has evolved rapidly - from early rule-based systems to contemporary machine learning and neural-network approaches. Generative AI (GenAI), a recent and particularly transformative subset, can create original content, synthesize information, and support complex decision-making. Tools such as

ChatGPT and DALL-E illustrate GenAI's capacity to automate creative tasks and augment cognitive work[1]. GenAI can either automate tasks or enhance them through human–AI collaboration[2]. According to Accenture, between 12% and 33% of employees' tasks may be automated and 11% to 42% augmented, with the potential to add USD 10.3 trillion to global GDP by 2038[3].

Despite this potential, GenAI cannot operate independently; its effectiveness depends on how humans deploy, supervise, and complement it[4]. The degree to which occupations are transformed varies considerably: some tasks may be highly automated, while others rely on augmented decision-making supported by AI systems.

Job satisfaction, in turn, is a central component of employee well-being and organizational performance[5,6]. It is commonly defined as a positive affective response to one's job role[7,8], shaped by the alignment between desired and actual work outcomes[9]. Although typically associated with monotonous work, job dissatisfaction may also arise in highly skilled white-collar roles when technological change disrupts established routines[10]. In financial services, where up to 70% of work tasks could be transformed by GenAI[3], the technology's impact on employee experience is therefore likely to differ across job types.

The aim of this research is to examine how generative AI influences job satisfaction among employees in the financial services sector in Poland. To address this, the study adopts socio-technical systems (STS) theory as its primary analytical lens, enabling a holistic understanding of how technological change interacts with social, organizational, and individual factors. The study analyzes how components of the technical subsystem (AI-related opportunities and technostress) and the social and organizational subsystems (leadership, team climate, organizational support) relate to job satisfaction, and whether these relationships vary with the susceptibility of different job roles to AI-driven change. This contributes to STS theory and offers practical insights for human-centered AI implementation.

The paper proceeds by outlining the theoretical background, presenting the empirical model and results, and concluding with a discussion of implications, limitations, and contributions.

Theoretical background

The rapid development of artificial intelligence (and generative AI in particular) is reshaping how work is organized and carried out. As these tools become part of everyday practices in many sectors, it is increasingly important to understand how they affect employees and their experience of work. Job satisfaction remains closely linked to performance, engagement, and retention, so the way employees respond to new technologies has practical implications for organizations[5,6,11]. Exploring whether generative AI can support more satisfying work, and the conditions under which this occurs, offers useful insight for companies adapting to ongoing technological change.

Theories of job satisfaction have long emphasized the interplay of organizational, interpersonal, and individual factors. Situational occurrences theories, which explain how individuals determine their job satisfaction based on changes in situational factors[12,13], for instance, suggest that organizational context accounts for 40-60% of variance in employee attitudes[14]. Deriving from job characteristics there can be named five core job characteristics as conditions that lead to higher job satisfaction: task identity, task significance, skills variety, autonomy, and feedback[15]. Another framework suggests that the key factors of job satisfaction include availability of resources and tools, social support from leaders, and opportunities for professional development[16]. Additional studies have linked frequent communication and recognition[17] as well as personality of leaders and employees[18] to increased job satisfaction level. Sypniewska[19] further categorizes job satisfaction determinants into economic aspects, interpersonal relations, task diversity, and work conditions.

Generative artificial intelligence (AI) has a wide array of applications in financial services, revolutionizing the way organizations interact with customers and manage internal processes. For instance, AI-powered chatbots are deployed to enhance customer service by providing instant assistance and guiding employees in internal operations. Additionally, generative AI supports the creation of marketing and sales content, enabling financial institutions to communicate effectively and creatively with their clients. It also plays a critical role in automating repetitive tasks, such as document generation or compliance processes, reducing operational costs and increasing efficiency. Furthermore, it facilitates the personalization of customer offers, analyzing data to tailor products and services to individual preferences. Lastly, generative AI is instrumental in fraud detection and prevention, leveraging advanced algorithms to identify anomalies and patterns indicative of malicious activity, thus ensuring financial security and trust. These applications illustrate the transformative impact of generative AI across the financial sector[20]. At the same time, recent incidents (such as the Deloitte Australia GenAI scandal involving inappropriate reliance on AI-generated materials) highlight that rapid adoption also brings risks related to governance, accuracy, and professional standards. Over 2 years after the launch of ChatGPT, gen AI tools have already been used and allowed (with some obvious restrictions regarding data protection and privacy) in financial institutions. For example, Velo Bank in Poland has already implemented chatbots which augmented the work performed by financial advisors[21]. Therefore, it was reasonable to select this industry as an example and ask questions regarding the attitude and usage of gen AI tools to the employees, who are white collar and who should benefit from this technology the most[3].

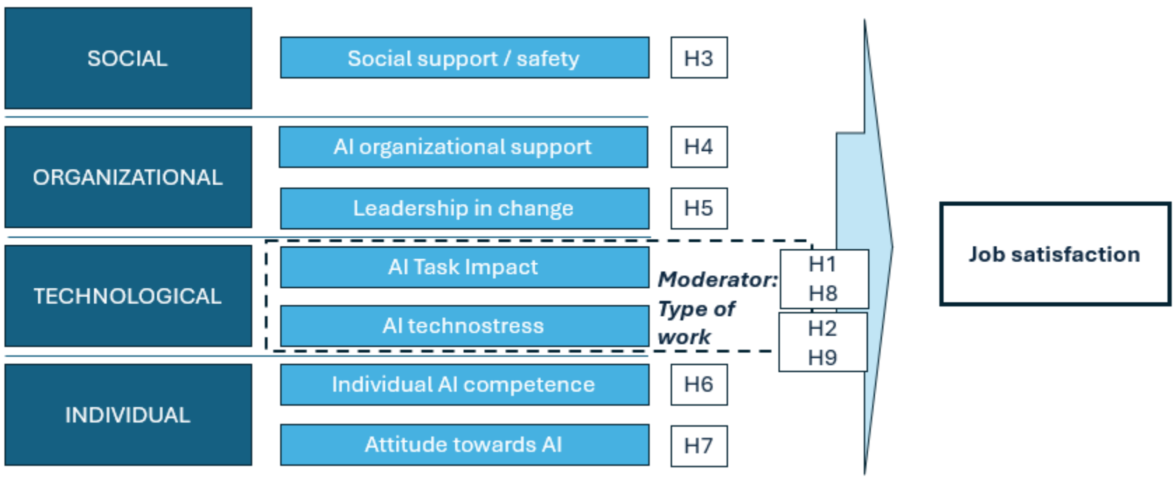
The impact of Generative AI (GenAI) on financial services is highly differentiated across roles though, with front-office and knowledge-intensive functions seeing the most profound transformation. Customer service, marketing, IT, and administrative support roles are expected to undergo the greatest shifts due to the automation of routine tasks, natural language generation, and decision support tools. According to McKinsey & Company[22], GenAI could automate up to 70% of customer service activities and significantly enhance personalization in marketing. Similarly, Deloitte[23]'s 2024 State of Generative AI in the Enterprise report highlights that while GenAI can enhance productivity and reduce manual workloads, it may also lead to role redefinition, especially in finance, compliance, and risk management areas. As these technologies become integrated, job satisfaction may diverge: some employees may experience greater efficiency and creative empowerment, while others, particularly in roles facing high automation risk, may feel uncertain about their future. The BCG[24] report underscores that this shift will require organizations to invest heavily in reskilling and upskilling programs to prepare their workforce for augmented roles rather than replaced ones. Training will be essential not only to ensure technical proficiency but also to foster adaptability and trust in AI systems. As GenAI continues to evolve, its uneven impact across job functions will shape organizational culture, talent strategies, and employee expectations. This variation suggests that employees may experience and cope with GenAI differently, making the type of occupation a meaningful moderator of the relationship between GenAI use and job satisfaction.

Despite growing interest in generative artificial intelligence (GenAI), empirical research on how employees experience and evaluate its integration, particularly in relation to job satisfaction, remains limited and theoretically fragmented[25,26]. Prior research on technology adoption and job satisfaction reports mixed findings, reflecting the fact that technological change may be interpreted either as an opportunity or as a threat[27]. For example, studies on robotics and automation highlight fear, uncertainty, and declining satisfaction[28,29], whereas other research documents positive effects of digital technologies on job satisfaction through improved communication, access to information, and task enrichment, particularly among white-collar workers[30,31].

Because GenAI tools have only recently become widely available, evidence on their relationship with job satisfaction is still emerging[32]. Importantly, GenAI differs from earlier forms of automation by combining task automation with augmentation and close human–AI collaboration. Recent studies suggest that learning to work with GenAI is not necessarily experienced as burdensome and may even enhance engagement by streamlining workflows and reducing routine work[33,34]. At the same time, human-related factors such as acceptance and organizational support have been identified as critical barriers to successful GenAI implementation[35]. Without adequate alignment between technology, work design and organizational context, expected benefits such as augmented decision-making or improved knowledge access may fail to materialize[36]. Understanding how employees experience these dynamics, and how they translate into job satisfaction, is therefore essential, particularly in knowledge-intensive sectors such as financial services.

Taken together, this fragmented and mixed evidence highlights the need for a theoretical perspective that can account for both opportunity- and strain-related responses to generative AI within organizational contexts. Socio-Technical Systems (STS) theory provides the foundation for understanding how generative AI reshapes employee experiences by emphasizing the interdependence of technological, social, organizational, and individual subsystems[37]. The core principle of STS is joint optimization, meaning that positive outcomes emerge only when the technical subsystem (e.g., AI tools) is aligned with social relationships, organizational structures, and individual capacities[38]. Generative AI influences all four subsystem levels simultaneously, altering job tasks, collaboration norms, leadership responsibilities, and competence requirements; therefore, its influence on job satisfaction must be conceptualized holistically through STS rather than as a purely technological effect[39]. Based on this perspective, we develop the following theoretical model and hypotheses.

Figure 1. Conceptual framework



Source: own elaboration

Generative AI offers employees new opportunities by reducing routine work and enabling engagement in more meaningful tasks. In STS theory terms, these positive affordances reflect an enhancement of the technical subsystem that can improve work experience when appropriately supported by the other subsystems. Consistent with coping theory (while coping theory is not directly operationalized in the measurement model, it offers a valuable interpretive lens for understanding how employees appraise AI-related changes as opportunities or threats), such opportunities encourage a challenge appraisal, whereby employees interpret AI as beneficial and empowering[27]. When employees perceive AI as a facilitator of enriched work, job satisfaction is likely to increase.

H1: *Perceived AI-related task opportunities are positively associated with job satisfaction.*

However, recent research suggests that such positive effects are highly contingent on task structure and coordination requirements. Guffler et al.[40] show that generative AI can also disrupt teamwork and role clarity, potentially undermining job satisfaction when social and task interdependencies are not adequately aligned. Generative AI may also generate concerns related to job security, accuracy of AI outputs, increased cognitive load, or disruptions caused by regulatory constraints[41]. From an STS perspective, such negative perceptions arise when the technical subsystem evolves faster than the social and organizational subsystems can adjust, resulting in socio-technical misalignment and employee strain[38]. Coping theory similarly describes these responses as threat appraisals, which lead employees to experience anxiety and reduced satisfaction when facing technological uncertainty[27,42]. Accordingly, higher perceived AI-related threats should reduce job satisfaction.

H2: *Perceived AI-related threats and technostress are negatively associated with job satisfaction.*

The social subsystem (including team relations and psychological safety) plays a central role in helping employees interpret technological change. Positive team climates facilitate open communication, knowledge sharing, and mutual reassurance, allowing employees to integrate AI tools with reduced uncertainty[43,44]. Research shows that when colleagues and leaders model constructive use of AI, employees are more likely to adopt problem-focused coping and view the technology as manageable and beneficial[39]. Therefore, supportive team environments should foster higher job satisfaction during AI adoption.

H3: *Higher levels of social support and safety are positively associated with job satisfaction.*

Organizational investments in AI training, access to experts, and assistance in making sense of technological changes help employees adapt effectively to AI-enabled work environments. In STS, this constitutes structural alignment, ensuring that the organization adjusts its processes and resources to match the capabilities and demands of the technical subsystem. Such support reduces ambiguity, strengthens coping resources, and enables employees to maintain confidence during transformation[41,36] Consequently, strong organizational support for AI is expected to improve job satisfaction.

H4: *Organizational support for AI is positively associated with job satisfaction.*

Leaders act as integrators in STS, ensuring that technological change is synchronized with organizational practices and employee expectations. Leadership behaviors such as articulating a clear vision, communicating changes transparently, modelling openness to AI, and adjusting strategies over time foster stability and trust[38]. Empirical studies show that employees respond more positively to AI when leaders provide guidance and consistency, which facilitates constructive coping and enhances satisfaction[39]. Effective leadership therefore strengthens job satisfaction during AI-driven transformation.

H5: *Perceived leadership effectiveness in managing AI-driven change is positively associated with job satisfaction.*

Employees' confidence in understanding and learning AI-related skills is a key factor in their ability to adapt to technological change. STS positions individual competence as a necessary condition for alignment between the technical subsystem and human capabilities. Supporting coping theory, higher technological competence promotes problem-focused coping and reduces perceptions of threat[45]. Therefore, employees with stronger AI competence are more likely to experience higher job satisfaction.

H6: *Individual competence in AI is positively associated with job satisfaction.*

Employees' emotional appraisal of AI such as feeling excited or optimistic shapes whether generative AI is interpreted as an opportunity or a threat. Positive attitudes support challenge-oriented coping and increase openness to experimentation, thereby improving the overall experience of AI-enabled work[27,41]. As part of the individual subsystem, emotional orientation colors employees' cognitive framing of technological change and influences satisfaction.

H7: *A positive attitude toward generative AI is positively associated with job satisfaction.*

Occupational exposure to generative AI varies substantially across roles, meaning that employees in highly AI-susceptible jobs encounter stronger technological disruption. STS suggests that the impact of the technical subsystem depends on the extent to which job structures are altered by technology. Recent research confirms that AI exposure acts as a boundary condition that intensifies both opportunity-related and threat-related reactions to AI[33,22]. Therefore, we expect job type to moderate relationships within the technical subsystem.

H8: *Job type moderates the association between AI task opportunities and job satisfaction, with a stronger association observed in highly AI-exposed roles.*

H9: J*ob type moderates the association between AI-related threats and job satisfaction, with a stronger negative association observed in highly AI-exposed roles.*

To sum up, in the age of AI, job satisfaction is shaped by the alignment between the social and technological aspects of the work environment, as emphasized by socio-technical systems theory. When employees receive adequate support, the introduction of generative AI is more likely to be experienced positively. The extent to which a role is exposed to AI-driven transformation may further influence these outcomes: employees whose tasks are highly affected by GenAI and who use these tools frequently may be better positioned to see their benefits, particularly when appropriate training reduces uncertainty and minimizes negative, emotion-based coping responses.

Materials and methods

In order verify the hypotheses and achieve the aim of this research, a quantitative analysis is performed. The model is built based on variables identified in the theoretical considerations above and the data have been collected in the survey among the employees of the financial services industry in Poland.

The financial sector in Poland is a vital pillar of the national economy, characterized by its dynamic growth, increasing digital maturity, and institutional stability. It comprises of key areas such as banking, insurance, capital markets, and a growing ecosystem of financial services including investment advisory, leasing, and fintech. Supervised by the Polish Financial Supervision Authority (KNF), the sector operates under robust regulatory frameworks aligned with EU standards, ensuring transparency and resilience. Technological advancement plays a central role in shaping the development of this sector. Polish financial institutions are actively adopting innovative solutions such as mobile banking, AI-driven risk assessment, robotic process automation (RPA), and generative AI (GenAI) to enhance efficiency, improve customer experience, and maintain competitiveness. Poland is among the European leaders in digital banking adoption, with a significant proportion of the population using online and mobile services[46]. The rise of fintech companies has further accelerated the sector's transformation by introducing agile, technology-first solutions and challenging traditional models. At the same time, the sector faces challenges including digital talent shortages, increasing cybersecurity demands, and the need for cultural adaptation to emerging technologies. Overall, technology acts as a key enabler of the sector's evolution, fundamentally reshaping financial services, business models, and the nature of work within the industry.

Data have been collected through a survey (CAVI method) among 433 employees of the financial services industry in Poland in August 2024. The sample was representative in terms of sub-industries (banking, insurance, capital markets) as well as size and types of companies and demographics of the respondents (Figure 2.).

Figure 2. Sample – employee survey – respondents characteristics

Source: own elaboration

The questionnaire captured employees' perceptions of social, organizational, technological, and individual working conditions related to the adoption of generative artificial intelligence (GenAI), as well as their overall job satisfaction. In line with prior research highlighting the perceptual and affective nature of job satisfaction[47], the job satisfaction question was placed at the beginning of the survey to minimize potential priming effects from subsequent, more detailed items. Job satisfaction (job_satisfaction) was measured using a five-point Likert scale.

The selection and grouping of explanatory variables follow socio-technical systems (STS) theory, which conceptualizes work outcomes as emerging from the interaction between social, organizational, technological, and individual subsystems. Within this overarching structure, specific constructs were informed by established theories of job satisfaction and work design, particularly the job characteristics model[15], situational theories of job satisfaction[48] and organizational resource-based perspectives[16].

Social subsystem variables capture employees' perceptions of interpersonal relations and psychological safety at work. In line with situational theories of job satisfaction, items assessed whether employees feel safe sharing ideas, whether their skills are recognized and utilized by colleagues, and whether achievements are acknowledged by leaders[48]. Observed use of generative AI by colleagues and executives was also included, reflecting social norms and modeling effects associated with the integration of new technologies in everyday work practices.

Organizational subsystem variables focus on leadership and structural support during technological change. Leadership in change was measured through items capturing the clarity of vision, effectiveness of communication, adaptability of strategies, role modeling, and leaders' competence in managing transformation. These items reflect organizational alignment and coordination mechanisms that facilitate joint optimization between social and technical subsystems. In addition, organizational support for AI adoption was captured through satisfaction with AI-related training, availability of upskilling opportunities, access to AI experts, and perceived organizational assistance in making sense of technological change, consistent with prior research emphasizing the role of resources and support in shaping job satisfaction[16].

The technological subsystem was operationalized through employees' perceptions of AI-related task impact and AI-related technostress. Task impact items capture the extent to which generative AI is perceived to automate routine tasks and enable engagement in more meaningful, interesting, or creative work, consistent with the job characteristics model's emphasis on task variety and task significance[15]. In contrast, technostress items reflect strain-based perceptions associated with generative AI, including stress and burnout, role and career insecurity, and concerns regarding the accuracy and reliability of AI outputs.

Individual subsystem variables capture employees' adaptive capacity in relation to generative AI. Individual AI competence was measured through self-assessed confidence in acquiring AI-related skills and understanding how generative AI works. Attitude toward AI reflects employees' emotional orientation toward AI-driven changes, captured through excitement and optimism regarding AI's implications for their career prospects. These variables represent individual-level conditions that shape how technological change is appraised and experienced within the broader socio-technical system.

Age and gender were included as control variables. Additionally, type of work was introduced as a binary moderator capturing differential exposure to AI-susceptible task structures rather than occupational status per se. This variable allows for testing whether the relationships between AI-related task characteristics and job satisfaction vary depending on the extent to which employees' roles are affected by generative AI.

An overview of all survey items and their corresponding constructs is presented in Figure 3. The variables have been computed as the mean values of the underlying constructs (statements / questions).

Figure 3. Questions selected to constitute variables.

Variable	Statement / Question	Scale
SOCIAL: Social support / safety (Social_support)	I feel safe sharing ideas, taking risks, and raising difficult issues	1(I do not agree at all) - 5 (I do fully agree)
	When working with my team members, my skills are appreciated and used	1-5
	Executives take note of employee and team achievements to maintain engagement	1-5
	My colleagues regularly use Generative Artificial Intelligence	1-5
	My company's executives regularly use Generative Artificial Intelligence	1-5
ORGANIZATIONAL: Leadership in change (Leadership_mgmt)	Executives Present a Clear and Convincing Vision and Purpose for Change	1-5
	Executives are effective in communicating the need for change and its beneficial effects on teams	1-5
	Executives continuously evaluate and adapt strategies and actions to the objectives of the	1-5
	Executives set an example of desirable behaviors, such as openness to change	1-5
	Executives have the necessary skills required to effectively implement change	1-5
ORGANIZATIONAL: AI organizational support (Org_support_AI)	I feel supported by the company in finding personal meaning in change	1-5
	What is your level of satisfaction with training and support from your employer in implementing AI solutions?	1 (very low satisfaction) - 5 (very high satisfaction)
	My company offers training and upskilling opportunities in Generative Artificial Intelligence	1-5

	My company employs experts in Generative Artificial Intelligence	1-5
TECHNOLOGICAL: AI task impact (AI_task_opportunity)	Generative Artificial Intelligence will allow me to automate my routine tasks	1-5
	Generative AI will allow me to work on more meaningful, interesting and creative tasks	1-5
TECHNOLOGICAL: AI technostress (AI_technostress)	Generative Artificial Intelligence will increase my stress and burnout	1-5
	I feel less safe and confident in my role because of Generative Artificial Intelligence	1-5
	I feel less safe and confident about my career opportunities because of Generative AI	1-5
	I'm worried about the accuracy and reliability of the results of Generative Artificial Intelligence	1-5
INDIVIDUAL: individual AI competence (Individual_compt_AI)	I am confident that I can gain the skills and knowledge needed to use Generative Artificial Intelligence in my work	1-5
	I have a high level of understanding of how Generative Artificial Intelligence works	1-5
INDIVIDUAL: attitude towards AI (Positive_attitude)	I'm excited to see how Generative AI will change my career prospects	1-5
Type of work (Type_of_work)		0 (low impact) -1 (high impact)
OUTCOME: Job satisfaction		1(very low satisfaction) - 5 (very high satisfaction)

Source: own elaboration

To ensure the internal consistency and reliability of the data used in the research, the Cronbach's alpha coefficient was evaluated. The value of Cronbach's alpha value was found to be 0.77, which exceeds the usually accepted threshold of 0.70, suggesting the internal consistency of the survey, collected data.

Moreover, an analysis of multicollinearity was conducted to ensure that the independent variables were not too highly correlated (i.e., collinear); the Variance Inflation Factor (VIF) was calculated to detect potential redundancies within the set of predictors. The values of particular VIF is presented in Figure 4. All of the VIF values remained below the conservative threshold of 5, with the highest value being 4.38 for Social_support. These results provide evidence that the problem of multicollinearity is not present in the dataset.

Figure 4. Variance Inflation Factor values

Attribute	**VIF**
Social_support	4.38
Leadership_mgmt	3.48
Org_support_AI	3.19
AI_task_opportunity	2.25
Positive_attitude	2.14
Individual_compt_AI	2.10
AI_technostress	1.21
Age_log	1.04

Gender	1.04
Type_of_work	1.01

Source: own elaboration.

The classification of job types according to their susceptibility to transformation by generative AI builds on a long tradition of research demonstrating that occupations differ substantially in their exposure to technological change. Seminal task-based studies show that the potential impact of new technologies varies systematically across occupations depending on task composition[49]. More recent research indicates that occupations characterized by intensive language processing, information handling, and routine content generation exhibit higher exposure to large language models and generative AI tools[50].

Following this task-based perspective, roles primarily centered on customer service, IT and technology, marketing and communication, media and information, and digitization and automation were classified as high AI exposure (coded as 1). These functions rely heavily on tasks that overlap with core capabilities of generative AI and are therefore more likely to experience task-level transformation and augmentation. In contrast, roles such as administration, procurement and logistics, finance and audit, human resources, sales, and legal were classified as lower AI exposure (coded as 0). Although these functions involve cognitive and language-based activities, they typically require higher levels of contextual judgment, regulatory compliance, and human oversight, which currently limit the extent of task automation[23,24].

Importantly, this classification does not imply deterministic automation outcomes but serves as a proxy for differential task-level exposure to generative AI, consistent with prior research on occupational heterogeneity in technological change[22]. Accordingly, type of work is employed as a moderator to examine whether the relationship between AI-related task characteristics and job satisfaction varies with the intensity of GenAI exposure.

Results

An ordered logit model was chosen as the dependent variable, Job Satisfaction (job_satisfaction), is measured on a five-point ordinal scale. Model allows to account for the inherent ranking of the categories while estimating the probability of a response falling into each category. Unlike multinomial logistic regression, ordered logit preserves information about the order in the response categories, which is essential when the distance between categories is unknown, but their sequence is meaningful. The general ordered logit model equation (without moderator), for ten exogenous attributes is as follows:

$$\log\left(\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right) = \mu_j - \sum_{i=1}^{10} \beta_i X_i \qquad (1)$$

where μ_j is the j-th cut (also referred to as threshold), β_i is the parameter corresponding to the i-th attribute. The logit function (lefthand side of the equation 1) is a function of the 10 attributes, namely:

1. Social_support
2. Leadership_mgmt
3. Org_support_AI
4. AI_task_opportunity
5. Positive_attitude
6. Individual_compt_AI
7. AI_technostress
8. Age_log
9. Gender

10. Type_of_work

The observed outcome Y is categorized as follows:

$$\begin{cases} Y = 1, & \text{if } Y^* \leq \mu_1 \\ Y = 2, & \text{if } \mu_1 < Y^* \leq \mu_2 \\ Y = 3, & \text{if } \mu_2 < Y^* \leq \mu_3 \\ Y = 4, & \text{if } \mu_3 < Y^* \leq \mu_4 \\ Y = 5, & \text{if } \mu_4 < Y^* \end{cases}$$

Estimation of the model has been performed in python (statsmodels.miscmodels.ordinal_model package).

Figure 5. Estimation of the Model 1

Attribute	**Coefficient**	**Std. error**	**p-value**
Leadership_mgmt	0.52***	0.18	0.004
Social_support	0.34	0.22	0.113
Org_support_AI	0.48***	0.17	0.005
AI_task_opportunity	0.15	0.14	0.289
AI_technostress	-0.13	0.11	0.256
Positive_attitude	-0.20*	0.12	0.090
Individual_compt_AI	0.05	0.14	0.737
Age_log	-0.43	0.32	0.179
Gender	0.30	0.19	0.112
Type_of_work	-0.10	0.18	0.583

Model 1: Ordered Logit, using observations 1-433

Dependent variable: job_satisfaction
Source: own elaboration.

The ordered logit model indicates that several factors are statistically significant regarding job satisfaction. As of the results, the leadership of the organization and its openness for AI-related changes, comoves positively with the satisfaction of employees (Leadership_mgmt); also, the organizational support for AI-driven changes and implementations positively correlates with satisfaction (Org_support_AI).

On the other hand, the positive attitude of employees is negatively associated with satisfaction (Positive_attitude). The odds ratios are presented below (Figure 6.)

Figure 6. Odds ratios for the ordered logit model.

Attribute	**Odds ratio**
Leadership_mgmt	1.69
Org_support_AI	1.62
Social_support	1.41
Gender	1.35
AI_task_opportunity	1.16
Individual_compt_AI	1.05
Type_of_work	0.90
AI_technostress	0.88
Positive_attitude	0.82

Age_log	0.65

Model 1: Ordered Logit, using observations 1-433

Dependent variable: job_satisfaction
Source: own elaboration.

The odds ratios from Model 1 offer a clear interpretation of how various factors influence the likelihood of reporting higher job satisfaction. A one-unit increase in Leadership_mgmt raises the odds of being in a higher satisfaction category by approximately 69%, while organizational support increases those odds by about 62%. Conversely, greater positive attitude decreases the odds of higher satisfaction by around 18%.

Before accepting the results of the ordered logit model, it is essential to verify whether the proportional odds assumption (also known as the parallel lines assumption) holds. This assumption states that the relationship between each predictor and the logit function of being in a higher category of the dependent variable is constant across all thresholds, see Agresti[51]. Violations of this assumption may lead to biased estimates and incorrect conclusions, particularly when the effects of predictors differ at various levels of the outcome variable. To assess the validity of this assumption in the context of this model - including interaction terms (moderators) - a Brant test simulation has been performed. It estimates separate binary logistic regressions for each threshold of the dependent variable (job_satisfaction). This allows us to observe whether the estimated coefficients remain stable across increasing satisfaction levels.

Figure 7. Brant test for the Model 1.

Attribute	χ^2	**p-value**
Const.	25.83	0.684
Leadership_mgmt	2.68	0.444
Social_support	3.36	0.339
Org_support_AI	4.05	0.256
AI_task_opportunity	1.36	0.715
AI_technostress	2.17	0.539
Positive_attitude	0.37	0.947
Individual_compt_AI	5.54	0.136
Age_log	1.03	0.793
Gender	5.49	0.139
Type_of_work	3.88	0.275

Model 1: Ordered, using observations 1-433

Dependent variable: job_satisfaction
Source: own elaboration.

The results of the Brant test simulation indicate that the proportional odds assumption is met for all of the predictors included in Model 1. As the proportional odds assumption held it was decided to retain the ordered logit model in this analysis.

The inclusion of Type_of_work as a moderator (interaction with other attribute) is theoretically grounded in the differential exposure of occupational roles to AI-driven transformation. By incorporating Type_of_work as a interaction with AI_technostress and AI_task_opportunity, the model tests whether the effects of interaction between those attributed occur.

Figure 8. Estimation of the Model 2 with moderator

Attribute	Coefficient	Std. error	p-value
Leadership_mgmt	0.51***	0.18	0.006
Social_support	0.33	0.22	0.129
Org_support_AI	0.47***	0.18	0.008
AI_task_opportunity	0.09	0.16	0.574
AI_technostress	0.06	0.14	0.697
Positive_attitude	-0.19*	0.12	0.095
Individual_compt_AI	0.06	0.14	0.646
Age_log	-0.42	0.32	0.193
Gender	0.30	0.19	0.104
Type_of_work	0.73	0.74	0.324
Type_of_work_&_AI_technostress	-0.44**	0.22	0.047
Type_of_work_&_AI_task_opportunity	0.17	0.21	0.407

Model 2: Ordered Logit with moderator, using observations 1-433

Dependent variable: job_satisfaction
Source: own elaboration.

The results of Model 2 reveal that type of work significantly shaped by both organizational factors and employees' experiences with generative AI. Interestingly, once moderator variables are introduced, the interaction with AI_technostress becomes statistically significant. On the following Figure 9 the odds ratios for the ordered logit model are presented.

Figure 9. Odds ratios for the ordered logit model with moderator.

Attribute	Odds ratio
Type_of_work	2.07
Leadership_mgmt	1.66
Org_support_AI	1.59
Social_support	1.39
Gender	1.35
Type_of_work_&_AI_task_opportunity	1.19
AI_task_opportunity	1.09
AI_technostress	1.06
Individual_compt_AI	1.06
Positive_attitude	0.82
Age_log	0.66
Type_of_work_&_AI_technostress	0.64

Model 2: Ordered Logit with moderator, using observations 1-433

Dependent variable: job_satisfaction
Source: own elaboration.

Similarly to Model 1, the proportional odds assumption was verified, and results presented in the Figure 10.

Figure 10. Brant test for the Model 2.

Attribute	χ^2	p-value

Omnibus	26.43	0.878
Leadership_mgmt	0.40	0.940
Social_support	2.64	0.450
Org_support_AI	4.11	0.250
AI_task_opportunity	1.57	0.666
AI_technostress	1.95	0.583
Positive_attitude	0.18	0.981
Individual_compt_AI	5.82	0.121
Wiek_log	2.51	0.474
Płec	5.17	0.160
Type_of_work	2.86	0.414
Type_of_work_&_AI_technostress	2.66	0.448
Type_of_work_&_AI_task_opportunity	3.75	0.290

Model 2: Ordered, using observations 1-433

Dependent variable: job_satisfaction
Source: own elaboration.

The results of the Brant test simulation indicate that the proportional odds assumption is met for all the predictors included in Model 1 as well as the interactions between Type_of_work with AI_technostress and AI_task_opportunity. As the proportional odds assumption held it was decided to retain the ordered logit model in this analysis. This decision is justified on both theoretical and empirical grounds. First, the dependent variable - job_satisfaction is clearly ordinal in nature, and preserving this structure is essential for meaningful interpretation. Second, the Brant test simulation showed that the proportional odds assumption holds for all the predictors

Discussion

This study examines job satisfaction in the context of generative artificial intelligence (GenAI) adoption through the lens of socio-technical systems (STS) theory. Within this perspective, job satisfaction is not treated as a direct consequence of technology use, but as an emergent outcome shaped by the alignment between technological change and the surrounding social, organizational, and individual subsystems[37,38]. The results support this view by showing that job satisfaction is more strongly associated with organizational and leadership-related conditions than with individual orientations toward AI.

Across model specifications, leadership effectiveness in managing change and organizational support for AI are positively and consistently associated with job satisfaction. This finding reinforces earlier research emphasizing that organizational structures, leadership practices, and resource availability play a central role in shaping employee attitudes during periods of technological transformation[14,36]. In line with STS assumptions, GenAI does not appear to influence employee satisfaction in isolation; instead, its implications depend on how it is embedded in organizational routines and supported by managerial practices.

The findings further highlight that the effects of GenAI are heterogeneous rather than uniform. While AI-related task opportunities are broadly perceived across job types, AI-related technostress is more strongly associated with lower job satisfaction among employees in roles with higher exposure to AI-driven task transformation. This asymmetry aligns with prior research showing that technological change tends to amplify strain in roles facing greater task disruption, even when potential efficiency gains are visible[27,26,52]. Together, these patterns underscore that employee experiences of GenAI are contingent on socio-technical alignment rather than on the technology itself.

Effective leadership appears to function as a key integrative mechanism, helping employees make sense of AI-related changes and reducing uncertainty associated with new technologies. Clear communication, visible commitment, and adaptive change management practices likely provide employees with interpretive frames that stabilize work experiences during periods of disruption. This aligns with prior research showing that leadership and organizational resources are critical determinants of employee attitudes under conditions of technological and organizational change[14,36].

Similarly, organizational support for AI, captured through access to training, upskilling opportunities, expert support, and assistance in interpreting technological change, emerges as a structural condition that enhances job satisfaction. Rather than acting as a purely technical input, such support reflects the organization's capacity to align technological innovation with human needs and work practices. This finding is consistent with earlier evidence that investments in employee development and supportive infrastructures buffer the potentially adverse effects of new technologies and contribute to more positive work-related outcomes[53,52,42].

Consistent with Hypotheses H4 and H5, these findings indicate that leadership effectiveness and organizational support for AI are positively associated with job satisfaction.

A key insight of the study is the asymmetric role of AI-related opportunities and AI-related technostress in shaping job satisfaction, particularly under conditions of differential task exposure. While perceived AI-related task opportunities are broadly visible across job types, AI-related technostress exhibits a conditional effect: its negative association with job satisfaction is significantly stronger among employees in roles with higher exposure to AI-driven task transformation. This finding highlights that the disruptive aspects of generative AI are not evenly distributed across the workforce, even when potential efficiency gains are widely recognized.

From a socio-technical systems perspective, this asymmetry suggests that technological opportunities and technological strain operate through different mechanisms. AI-related task opportunities appear to be perceived as general features of technological progress, whereas technostress reflects localized misalignment between the technical subsystem and existing work structures. In highly exposed roles, increased stress, insecurity, and concerns about reliability may accumulate more quickly, intensifying negative work experiences when organizational and social buffers are insufficient. This pattern reflects the broader automation–augmentation paradox, whereby AI simultaneously enhances performance while introducing new coordination demands and psychological strain[54].

This interpretation is consistent with research emphasizing that employees' responses to new technologies depend on how technological change is appraised and integrated into daily work practices. Prior studies show that technological innovations may generate perceptions of opportunity and threat at the same time, with strain-related responses emerging more strongly when task disruption is high[27,52].

Consistent with Hypothesis H9, the results indicate that job type moderates the relationship between AI-related technostress and job satisfaction, whereas no comparable moderation effect is observed for AI-related task opportunities (contrary to H8). This finding suggests that under conditions of high AI exposure, mitigating strain may be more critical for maintaining job satisfaction than amplifying perceived opportunities. It also reinforces broader arguments that work design and organizational conditions shape employee responses to advanced technologies more strongly than individual optimism or perceived efficiency gains alone[55,26,36].

In contrast to organizational and technological factors, individual-level attitudes toward generative AI play a more limited role in shaping job satisfaction. The results indicate that a positive attitude toward AI is not associated with higher job satisfaction and is, if anything, weakly negatively related. This finding suggests that individual optimism or enthusiasm toward AI does not automatically translate into more favorable work experiences when broader socio-technical conditions are not fully aligned.

From a socio-technical systems perspective, this pattern reinforces the idea that individual orientations cannot compensate for shortcomings in organizational design or technological integration. Even when employees are excited about AI, misalignment between task demands, work structures, and organizational support may constrain the extent to which such attitudes can be converted into positive outcomes. This interpretation aligns with prior research emphasizing that work design and organizational context exert a stronger influence on employee well-being than individual dispositions alone during periods of technological change[27,26].

Viewed through the lens of coping theory, the findings suggest that positive attitudes toward AI reflect a general openness to technological change rather than effective coping in practice. While optimism may facilitate initial engagement with new technologies, it does not necessarily reduce strain or uncertainty when employees face intensified task disruption or increased performance pressure. In this sense, coping resources appear to be located primarily at the organizational level—through leadership, training, and structural support—rather than at the level of individual affect. This pattern may reflect the fact that employees who report higher enthusiasm about AI also hold higher expectations that are not fully supported by organizational conditions, a dynamic consistent with evidence that lower AI literacy is linked to greater AI receptivity due to perceptions of AI as "magical"[56].

Consistent with Hypothesis H7, the results therefore do not support a strong positive association between individual attitudes toward AI and job satisfaction. Instead, they underscore that successful adaptation to generative AI depends less on individual enthusiasm and more on the availability of organizational and social resources that enable problem-focused coping and mitigate AI-related strain[52,42,36].

Taken together, the findings highlight that job satisfaction in the context of generative AI adoption is best understood as an outcome of socio-technical alignment rather than as a direct response to technology itself. Across the analyses, organizational and leadership-related factors emerge as the most consistent correlates of job satisfaction, while technological change introduces both opportunity and strain that are unevenly distributed across job roles. In particular, AI-related technostress proves to be more consequential for employees in highly exposed roles, whereas perceived task opportunities are more uniformly recognized and less sensitive to occupational differences.

The results further suggest that individual-level attitudes toward AI play a secondary role. Positive orientations toward generative AI do not, on their own, translate into higher job satisfaction, underscoring the limits of individual enthusiasm in the absence of supportive organizational conditions. From a socio-technical perspective, this pattern reinforces the primacy of organizational design, leadership, and support structures in shaping how employees experience AI-driven transformation.

Overall, the study contributes to the emerging literature on generative AI and work by demonstrating that employee outcomes depend less on the presence of advanced technologies and more on how these technologies are embedded within existing work systems. By integrating insights from socio-technical systems theory and research on technostress and coping, the findings help explain why similar AI tools may coexist with both positive and negative employee experiences within the same industry. This synthesis provides a foundation for the practical implications discussed in the following section.

Conclusion and practical implications

This study examined how employees in the financial services industry experience the integration of generative artificial intelligence (GenAI) and how these experiences relate to job satisfaction. Drawing on socio-technical systems theory, the analysis shows that job satisfaction in the context of GenAI adoption is not a direct outcome of technology use, but rather an emergent result of alignment between technological change and organizational, social, and individual conditions. By empirically disentangling these interdependencies, the study contributes to a more nuanced understanding of employee responses to generative AI in knowledge-intensive work.

The findings extend prior research that has documented generally positive associations between generative AI adoption and employee outcomes at an aggregate level[57]. While such studies highlight the potential of GenAI to enhance work experiences, the present results demonstrate that these benefits are neither automatic nor uniform. Instead, they are contingent on organizational context and task exposure.

From a practical perspective, these findings suggest that organizations seeking to maintain or enhance job satisfaction during GenAI adoption should prioritize organizational and managerial conditions over technology-centric interventions alone. Investments in leadership capabilities and organizational support structures (e.g. training, access to expertise, sense-making around AI-driven change) appear critical for stabilizing employee experiences. Especially in roles facing high AI exposure, mitigating technostress may be more important than emphasizing potential efficiency gains or productivity improvements.

For managers in financial services and other knowledge-intensive sectors, the results highlight that successful GenAI implementation is as much a human and organizational challenge as it is a technical one. Framing AI as an augmentative tool must be accompanied by concrete organizational practices that reduce uncertainty, support adaptation, and align new technologies with existing work systems. Without such alignment, even advanced and potentially beneficial AI tools may coexist with reduced job satisfaction among key employee groups.

In the context of Poland's rapidly digitizing financial sector, these findings are particularly salient. As AI adoption accelerates amid documented skill shortages[1], continuous upskilling and organizational support become central to sustaining employee satisfaction. The results suggest that investments in training, transparent communication, and change management are not merely complementary to AI implementation but integral to it. Especially in highly regulated financial environments, aligning technological innovation with human capabilities may help organizations mitigate AI-related strain while enabling employees to adapt and contribute productively.

Overall, the study underscores that generative AI does not determine employee outcomes on its own. Rather, job satisfaction in the age of AI depends on how organizations design, lead, and support socio-technical change. By showing that job satisfaction under generative AI adoption depends on socio-technical alignment rather than on technology alone, the findings lend empirical support to broader calls for human-centered and symbiotic approaches to AI design and implementation[58]. By moving beyond aggregate narratives of AI-driven improvement, the findings offer both scholars and practitioners a more differentiated view of when and why generative AI contributes to positive work experiences.

Limitations and future research

While this study offers insights into job satisfaction under generative AI adoption, several limitations should be acknowledged.

First, the analysis is based on data collected from employees in the financial services sector in Poland. Poland represents a large, rapidly digitizing EU economy with a modernizing financial industry, making it a relevant setting for studying AI-driven work transformation. At the same time, institutional, cultural, and labor-market conditions may differ across countries. Prior research suggests

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[1] https://www.trade.gov.pl/en/news/the-ai-revolution-on-the-polish-labour-market-who-will-win-and-who-will-lose/; https://www.careersinpoland.com/article/news/staffing-shortages-in-the-financial-sector-in-poland-on-technology-upskilling-work-life-balance-and-employees-vs-ai

that the organizational and employee-level consequences of digital transformation are context dependent[26]. Future studies could therefore replicate this research in other national contexts or industries to assess the robustness of the observed patterns.

Second, the study relies on cross-sectional survey data, which limits the ability to draw causal conclusions. While the analysis identifies robust associations between organizational conditions, AI-related strain, and job satisfaction, reverse causality and unobserved heterogeneity cannot be fully ruled out – for example employees who are satisfied with their jobs are more eager to experiment with new technologies[59]. Longitudinal designs would allow future research to capture how employee appraisals and coping responses evolve as technologies are introduced and scaled over time, as emphasized in prior work on technology adaptation[27] (Beaudry & Pinsonneault, 2005).

Third, job satisfaction was measured using a single, global self-reported item. Single-item measures of overall job satisfaction are commonly used in large-scale surveys and are appropriate for capturing general affective evaluations of work[47]. Nevertheless, such measures do not allow for distinguishing between specific facets of satisfaction. Future research could employ multidimensional scales to examine whether generative AI differentially affects satisfaction with task content, job security, or career prospects.

Finally, while the study focuses on leadership and organizational support as key socio-technical resources, future research could further unpack how different forms of organizational support are enacted in practice. Qualitative or mixed-method approaches could provide deeper insight into how employees interpret AI-related change, training, and leadership communication in daily work settings, and whether these interpretations translate into longer-term outcomes such as engagement or turnover.

Declaration of interest statement

The authors declare that they have no conflict of interest.

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Note: Data were collected via a survey of white-collar employees in the financial services sector in Poland.