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SERVICE EMPLOYEES' APPRAISALS TOWARD ARTIFICIAL INTELLIGENCE, ROBOTICS AND AUTOMATION IN THE WORKPLACE – RESULTS OF EXPLORATORY AND CONFIRMATORY FACTOR ANALYSES

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Purpose: In view of the rapid advancements in artificial intelligence, robotics, and automation (AIRA) within service industries, it is crucial to understand how these technologies are perceived by organizational members to ensure their effective implementation. Therefore, the purpose of this paper is to gain insights into employees' appraisals toward AIRA in the workplace in service settings.
Design/methodology/approach: A quantitative approach was adopted, with data being collected via a self-administered online survey from 369 service employees in Poland. The sample was randomly split into two subsamples. The first subsample was used for exploratory factor analysis (EFA), while the second subsample was used for confirmatory factor analysis (CFA).
Findings: The results of the EFA and CFA indicate that the AIRA appraisal scale is multidimensional and consists of three subscales: resource appraisal toward AIRA, challenge appraisal toward AIRA, and hindrance appraisal toward AIRA. AIRA in the workplace is perceived by service employees predominantly as a resource, then as a challenge, and lastly as a hindrance.
Research limitations/implications: The data collection was based on the non-random sampling technique and the questionnaire was disseminated among employees of selected service industries in Poland, which limits the generalizability of the findings beyond the specific context of this research.
Originality/value: Drawing upon the refined job demands-resources (JD-R) model, the study provides a comprehensive and nuanced perspective on employees' perceptions of AIRA integration into service delivery processes. The proposed perspective is better suited to explain employees' attitudinal and behavioral reactions to AIRA-driven changes in the work environment.
Keywords: artificial intelligence, robotics and automation (AIRA), workplace, appraisal, service employees, factor analysis.
Category of the paper: Research paper.

1. Introduction

In recent decades, the implementation of digital technologies, particularly artificial intelligence, robotics, and automation (AIRA), has profoundly transformed service workplaces and the nature of service jobs. A growing number of service organizations are opting to adopt AIRA with the objectives of reducing costs, enhancing operational efficiency, improving the customer experience, and optimizing the decision-making process (Buhalis et al., 2019; Borges et al., 2021). However, despite its increasing pervasiveness within service environments, research on service employees' attitudinal and behavioral reactions to AIRA adoption remains relatively scarce (Liang et al., 2022; Pereira et al., 2023; Hur, Shin, 2024). Furthermore, although some studies have highlighted the beneficial impacts of AIRA implementation on employees (e.g. Qiu et al., 2022; Li et al., 2024), the predominant focus of research has been on its detrimental consequences for work experiences and outcomes (e.g. Kong et al., 2021; Kang et al., 2024; Teng et al., 2024). A notable example of this approach is the concept of AIRA awareness, which – despite the neutrality of the term ”awareness” – has been widely used as a construct reflecting employees' concerns and commonly associated with job stress (e.g. Brougham, Haar, 2018; Zhou et al., 2024).

Researchers have posited that employees' perceptions of digital technologies exert a more substantial influence on predicting their work outcomes than the technology itself (Brougham, Haar, 2018; Ding, 2021). This assertion underscores the need to further explore AIRA appraisals in workplace context. Given the role of appraisals in shaping employees' attitudinal and behavioral responses, a comprehensive understanding of how intelligent technologies are perceived by organizational members is critical for developing effective strategies to facilitate AIRA adoption while concurrently mitigating risks and ensuring positive outcomes for employees. The purpose of the present paper is, therefore, to gain insights into employees' appraisals toward AIRA in the workplace in service settings.

To achieve the proposed purpose, the remainder of the paper is structured as follows. The next section delineates the job demands-resources (JD-R) model as the overarching framework for the study. Subsequent sections detail the methods employed and present the results obtained. Finally, the main findings are discussed, the limitations of the study are outlined and avenues for future research are suggested.

2. Theoretical grounding

A relevant framework to establish the theoretical foundation for AIRA appraisals in the workplace is the JD-R model (Demerouti et al., 2001; Bakker, Demerouti, 2017). The JD-R model is a unifying job design model that integrates various job stress and work motivation perspectives, elucidating the mechanisms through which individuals' workplace attitudes and behaviors are influenced by job characteristics (Bakker, Demerouti, 2017). These characteristics are properties of the work environment that can be classified into one of two broad categories: job demands and job resources. Job demands refer to the physical, psychological, social, or organizational aspects of the job that require sustained physical, cognitive, and/or emotional effort and are associated with certain physiological and/or psychological costs. Conversely, job resources refer to the physical, psychological, social, or organizational aspects of the job that are functional in achieving work-related goals, stimulate personal growth and development, and reduce job demands and the accompanying physiological and psychological costs (Demerouti et al., 2001).

Job demands and resources activate two distinct processes, namely a strain process and a motivation process. These processes give rise to divergent employees' attitudes and coping behaviors, yielding opposite effects on job performance. Specifically, job demands lead to work-related strain, as they deplete employees' physical, emotional, and cognitive resources; while job resources enhance work motivation, as they satisfy employees' basic psychological needs and foster dedication to work tasks by increasing the likelihood of successfully achieving one's work goals. Work-related strain has been shown to contribute to diminished job performance by diverting employees from work goals; in contrast, work motivation has been demonstrated to add to increased job performance by facilitating the adoption of goal-oriented behaviors. Finally, strain has been observed to perpetuate a loss cycle of maladaptive coping behaviors and job demands, which can further erode performance; meanwhile, motivation has been shown to initiate a gain cycle of proactive coping behaviors and job resources, thereby potentially enhancing performance (Bakker, Demerouti, 2017; Bakker et al., 2023).

An extension of the JD-R model (Crawford et al., 2010) posits that properties of the work environment falling under the job demand category are not homogeneous and can be further broken into two classes: threatening job demands (hindrances) and challenging job demands (challenges). Hindrances are defined as job demands that involve excessive or undesirable constraints that interfere with or inhibit an individual's ability to achieve valued goals. Conversely, challenges are defined as job demands that require effort but have the potential to engender feelings of fulfillment or achievement in an individual (Cavanaugh et al., 2000).

The proposed distinction is supported by cognitive appraisal theory (Lazarus, Folkman, 1984), which maintains that individuals, prior to implementing coping strategies, engage in primary and secondary appraisals when confronted with a novel situation. During a primary appraisal, individuals evaluate whether a particular encounter with the environment is relevant to their well-being and, if so, in what ways. When the encounter is deemed pertinent to the fulfillment of personal goals, values, or beliefs, a secondary appraisal ensues. At this stage, individuals assess their personal and situational resources, subsequently selecting actions that can be taken to overcome or prevent harm or to achieve benefit (Lazarus, Folkman, 1984). Encounters that are recognized to exceed one's resources are perceived as demands. Demands identified as thwarting goal attainment are appraised as threats (hindrances), whereas those identified as presenting an opportunity for gain are appraised as challenges (Crawford et al., 2010).

To summarize, according to the refined JD-R model, a strain process is initiated by all job demands, whether challenges or hindrances, because the increased effort associated with coping with demands results in resource depletion. A motivation process, however, is initiated both by job resources and challenging job demands, as they facilitate the achievement of valued goals and enhance the propensity to invest one's energy and abilities in the work task. In other words, while resources primarily impact job performance through a motivation pathway and hindrances primarily impact job performance through a strain pathway, challenges may contribute to job performance simultaneously through both pathways (Crawford et al., 2010; Van den Broeck et al., 2010).

It is important to note that employees' appraisals of specific work circumstances may not be uniform, as appraisals are subject to variation due to the unique characteristics of the individuals involved in this process. Furthermore, appraisal types are not inherently exclusive; a workplace situation may be, to varying degrees, interpreted in more than one way (Webster et al., 2011; Searle, Auton, 2015). Given this variability, using *a priori* categorizations of appraisals is deemed an invalid approach, as it does not accurately reflect employees' perceptions. Ultimately, it is the appraisals of situations, not the situations themselves, that explain employees' attitudinal and behavioral reactions.

In light of the aforementioned arguments, we posit that the implementation of AIRA in the workplace may be appraised by employees as a facilitating, challenging, or threatening work circumstance. Employees may perceive AIRA integration into service operations as a job resource because it can enhance their efficiency and effectiveness in work roles (Marinova et al., 2017) by eliminating some of the mundane and tedious tasks, thereby freeing up time to engage in more rewarding ones (Kassa, Worku, 2025), assisting in creative problem-solving (Jia et al., 2024), and reducing both physical and psychological workload and fatigue (Qiu et al., 2022). The adoption of AIRA in a service organization may be interpreted as a job challenge since employees may view the resulting pressure as an opportunity to adapt to the rapidly evolving work environment in the digital age (Liang et al., 2022), which positively affects their motivation to acquire new knowledge and skills (Ding, 2021) and fosters the satisfaction of their need for competence (Tan et al., 2024). Finally, AIRA implementation in service delivery processes may be viewed as a job hindrance due to its capacity to evoke fear of job replacement among employees (Brougham, Haar, 2018), which leads to an increased sense of job insecurity (Huang, Gursoy, 2024) and triggers workplace anxiety (Liu et al., 2024). Consequently, AIRA can be considered a double-edged sword, with the potential to result in a motivational and a taxing experience and, thereby, to enhance and impair employees' performance.

3. Methods

3.1. Instrument development

The AIRA appraisal scale was developed specifically for this study. To generate items that capture the specified domain of the construct under investigation, we conducted an extensive literature review on the effects of AIRA adoption on work outcomes at the individual level. This process was guided by the conceptual framework of the JD-R model proposed by Demerouti, Bakker, Nachreiner, and Schaufeli (2001) and later extended by Crawford, LePine, and Rich (2010). Based on the aforementioned review, we created a preliminary instrument consisting of 24 items. The item pool encompassed a range of consequences associated with the implementation of AIRA in the workplace, reflecting its appraisal as a resource, challenge, and hindrance.

A team of two researchers audited the initial list and evaluated each item based on its alignment with the conceptual interpretation of the construct. This procedure resulted in final list of 18 items that were subsequently included in the survey (Appendix). To ensure the relevance, clarity, and comprehensiveness of the questions and response options, we conducted a pre-test. Two experts in the field and five individuals representing the research population completed the questionnaire and provided feedback on its content. The pre-test revealed no significant issues related to wording or comprehension.

The final version of the survey instrument used in this study consisted of two sections. The first section gathered participants' opinions on the consequences of AIRA implementation in the workplace. All items were measured using a seven-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7). The second section collected socio-demographic and job-related data. Additionally, to enhance data quality, an attention check was incorporated, prompting participants to select a specific response option from the provided scale.

3.2. Participants and procedure

The target population in the present study were individuals working in the service industry. Specifically, we recruited employees from the accommodation, food and beverages, recreation, entertainment, and arts sectors in Poland. For data collection, an online survey was administered by an external company, Ariadna, which is the largest independent nationwide research panel in Poland. This company is recognized for its commitment to the highest standards of scientific rigor and integrity in its survey methodology.

The data was collected over the course of one month, in August 2024, and the respondents were selected using a non-probability sampling technique, namely voluntary response sampling. A total of 524 individuals participated in the study; however, 155 questionnaires were excluded from the analysis. Of these, 98 were excluded due to incorrect responses to the attention check question, 23 due to an extremely short completion time (less than one minute), and 34 due to a lack of variability in responses to items measuring the key variable. Consequently, the final analysis included the opinions of 369 respondents.

The majority of participants were female (65%), with the predominant age group being between 21 and 30 years old (34%). Most of the sample reported holding a higher education degree (52%). The respondents primarily occupied non-managerial positions (68%), held permanent employment contracts (51%), and had between one and three years of experience at their current workplace (25%). The largest proportion of the surveyed individuals worked in organizations with 10 to 49 employees (41%) and were employed in accommodation, food and beverages sector (59%) (Table 1).

Table 1.
Respondent profile (N = 369)

Variable	Category	N	%
Gender	Female	241	65.3
	Male	128	34.7
Age	20 years old or younger	26	7.0
	21-30 years old	127	34.4
	31-40 years old	120	32.5
	41-50 years old	72	19.5
	Over 50 years old	24	6.5
Education	Tertiary	192	52.0
	Secondary	155	42.0
	Vocational	20	5.4
	Primary	2	0.5
Job position	Managerial	118	32.0
	Non-managerial	251	68.1
Employment contract	Permanent contract	188	50.9
	Fixed-term contract	63	17.1
	Self-employment	32	8.7
	Mandate contract/ contract for specific work	84	22.7
	Other	2	0.5
Job tenure in current workplace	Less than three months	38	10.3
	Over 3 months to 1 year	60	16.3
	Over 1 year to 3 years	91	24.7
	Over 3 years to 5 years	62	16.8
	Over 5 years to 10 years	65	17.6
	Over ten years	53	14.4
Workplace size	Less than 10 employees	93	25.2
	10–49 employees	150	40.7
	50-249 employees	88	23.8
	Over 249 employees	38	10.3
Type of economic activity	Accommodation, food and beverages sector	216	58.5
	Recreation, entertainment, and arts sector	153	41.5

3.3. Data analysis

Data analysis was conducted using SPSS 29.0 and AMOS 26.0 statistical software. We performed both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to ascertain the factorial structure that would best represent service employees' appraisals toward AIRA in the workplace. Following established guidelines (Costello, Osborne, 2005; Worthington, Whittaker, 2006), the sample of 369 employees was randomly split in half – the first half was used for EFA (N = 185), while the second half was used for CFA (N = 184). The subsample sizes in both cases satisfied the criterion of a 10:1 subject-per-item ratio (Hair et al., 2014). Prior to conducting factor analyses, we checked the items for skewness and kurtosis in both subsamples separately. Neither the skewness nor the kurtosis coefficients exceeded the absolute value of 1.0, suggesting that the assumptions of a normal distribution were not violated (Hair et al., 2014).

We evaluated the suitability of the data for EFA using Bartlett's test of sphericity, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, and the single-variable measure of sampling adequacy (MSA). Statistical significance of Bartlett's test at a probability of 0.05 or less, a KMO value of 0.60 or higher, and MSA values of 0.50 or higher are indicative of sufficiently large relationships within the data set of interest, thereby justifying the implementation of factor analysis (Kaiser, Rice, 1974).

EFA was conducted employing the maximum likelihood extraction method followed by oblique rotation (Promax with Kaiser normalization). The decision regarding the number of factors to retain was made on the basis of eigenvalues, with factors exhibiting an initial eigenvalue of 1.0 or higher being kept. Additionally, we examined a scree plot to identify the inflection point in the curve connecting the eigenvalues of the factors, as well as percentage of variance explained, with solutions accounting for at least 60% of the total variance being deemed acceptable (Hair et al., 2014).

To evaluate scale items, we applied the following criteria: magnitude of item loadings, presence of cross loadings, and level of item communalities. For retaining an item, it is recommended that it load onto its primary factor above 0.40, load onto alternative factors below 0.30, and demonstrate a minimum difference of 0.20 between its primary and alternative factor loadings (Howard, 2016). Additionally, all items were assessed to ensure the deletion of those exhibiting communalities below 0.40 (Costello, Osbourne, 2005). To determine the reliability of the subscales, internal consistency was measured using Cronbach's alpha coefficient. The accepted standard for this index is 0.70 or above (Hair et al., 2014).

The factors extracted by EFA procedures were utilized as a base for creating the measurement model to be validated using CFA procedures. CFA was performed employing the maximum likelihood estimation method. The overall fit of the model was assessed with the following indices: the ratio of chi-square to degrees of freedom (χ^2/df), the comparative fit index (CFI), the Tucker–Lewis index (TLI), the incremental fit index (IFI), the standardized root mean square residual (SRMR), the root mean square error approximation (RMSEA), and the p-value for a close fit (PCLOSE). The model fit is considered to be good if χ^2/df falls below 2 (Tabachnick, Fidell, 2014), CFI, TLI and IFI exceed 0.95 (Hu, Bentler, 1999), SRMR is below 0.08 (Hu, Bentler, 1999), RMSEA is lower than 0.08 (MacCallum et al., 1996), and PCLOSE is greater than 0.05 (Schermelleh-Engel et al., 2003). In addition, the Akaike Information Criterion (AIC) and the Bayes Information Criterion (BIC) were employed to compare the alternative measurement models. For AIC and BIC, smaller values are indicative of better fitting models (Tabachnick, Fidell, 2014).

The next step involved assessing the scale's reliability and validity. To determine the reliability of the constructs, composite reliability (CR) scores were computed. The lower limit of acceptability for this index is 0.70 (Hair et al., 2014). In accordance with the recommendations by MacKenzie et al. (2011), the constructs' validity was ascertained through the content, convergent, and discriminant validity. The content validity was established based on a literature review that was used to create the items and on ratings of expert judges on the items' correspondence to the conceptually defined dimensions. Convergent validity was assessed by evaluating the magnitude and significance of loadings of indicators on their latent constructs, as well as by calculating the average variance extracted (AVE) in the indicators accounted for by the focal construct. A relationship with the latent construct that is significant and strong (above 0.60) (Bagozzi, Yi, 1988) and an AVE value greater than 0.50 (Fornell, Larcker, 1981) would suggest an adequate level of validity. Discriminant validity was determined by comparing the square root of AVE for each construct and the correlation coefficients between the focal construct and all the other constructs. Validity is established when the former exceeds the latter (Fornell, Larcker, 1981).

Based on the factor analyses results, we computed summated scores for each factor by averaging the included items. These scores were then utilized for the subsequent statistical analysis. Specifically, we employed a repeated measures analysis of variance and independent-samples t-tests to identify patterns of differences among the variables and among the subgroups of respondents.

4. Results

4.1. Exploratory factor analysis

Preliminary analysis showed that the data were suitable for EFA, as Bartlett's test of sphericity was significant ($\chi^2 = 2474.251$; df = 153; $p < 0.001$), a KMO value was greater than 0.60 (0.890), and the anti-image correlation matrix displayed MSA values above 0.50 for all items (0.710-0.951). We employed the maximum likelihood extraction method with Promax rotation (with Kaiser normalization), incorporating all 18 items of the AIRA appraisal scale.

The analysis indicated that the items reflected theoretically derived categories – one resource factor, one challenge factor, and one hindrance factor. All items demonstrated adequate loading on the intended construct (above 0.40), with the exception of one resource appraisal item and one challenge appraisal item, which exhibited substantial cross-loadings (above 0.30). Furthermore, an examination of item communalities revealed that one hindrance appraisal item had a communality coefficient of less than 0.40. Consequently, these three items were excluded from further analysis.

After scale purification, EFA was reiterated on the remaining 15 items. Once more, the factorability of the data was confirmed, as evidenced by a significant Bartlett's test of sphericity (χ^2 = 1902.274; df = 105; p < 0.001), a KMO value greater than 0.60 (0.869), and MSA values above 0.50 for all items (0.761-0.946). The maximum likelihood extraction method, followed by the Promax rotation with Kaiser normalization, was implemented, resulting in a three-factor solution. This solution was derived from initial eigenvalues (using Kaiser's criterion of 1), visual scree plot inspection, and amount of variance explained. Each of the three extracted factors comprised five items, collectively accounting for 64.34% of the total variance.

The communalities of all individual items ranged from 0.427 to 0.793, and the items exhibited adequate loading on the target factors (above 0.40) with no substantial cross-loadings. In particular, the loading values for the resource factor (F1) ranged from 0.589 to 0.935, for the challenge factor (F2) from 0.451 to 0.916, and for the hindrance factor (F3) from 0.649 to 0.822. Overall, the internal consistencies of the AIRA appraisal subscales were found to be high, with Cronbach's alpha coefficients consistently exceeding 0.70. Specifically, the alpha coefficients equaled 0.909 for the resource factor (F1), 0.881 for the challenge factor (F2), and 0.879 for the hindrance factor (F3). This finding substantiates the reliability of the constructs (Table 2).

Table 2.
Exploratory factor analysis results – development subsample (N = 185)

Item	Mean	Std Dev	Skewness	Kurtosis	Factor loading			Commu-nality
					F1	F2	F3	
AIRA2	4.58	1.545	-0.403	-0.177	0.674			0.611
AIRA3	4.36	1.396	-0.342	-0.043	0.786			0.739
AIRA4	4.26	1.500	-0.334	-0.200	0.935			0.772
AIRA5	3.95	1.475	-0.039	-0.226	0.772			0.653
AIRA6	4.30	1.473	-0.268	-0.013	0.589			0.652
AIRA7	4.23	1.296	-0.335	0.474		0.640		0.507
AIRA8	4.21	1.277	-0.234	0.478		0.848		0.733
AIRA9	4.18	1.393	-0.275	0.073		0.916		0.793
AIRA11	4.16	1.495	-0.133	-0.288		0.641		0.660
AIRA12	3.81	1.446	-0.091	-0.185		0.451		0.432
AIRA13	3.40	1.720	0.172	-0.850			0.770	0.610
AIRA14	3.25	1.586	0.392	-0.417			0.820	0.685
AIRA15	3.42	1.620	0.241	-0.568			0.822	0.709
AIRA16	3.39	1.672	0.309	-0.606			0.811	0.669
AIRA18	4.20	1.680	-0.202	-0.666			0.649	0.427
Cronbach's alpha					0.909	0.881	0.879	

Sum of squared loadings					5.863	3.087	0.702	
Variance explained (%)					39.083	20.580	4.677	

4.2. Confirmatory factor analysis

In order to determine whether the three-factor structure obtained on the development subsample using EFA could be confirmed on the validation subsample, we performed CFA. The goodness-of-fit statistics were evaluated based on the model in which all latent variables were correlated. An inspection of the goodness-of-fit indices for the proposed model suggests that it adequately represents the data, as $\chi^2 = 128.164$, df = 72, χ^2/df = 1.780, CFI = 0.974, TLI = 0.961, IFI = 0.974, SRMR = 0.053, RMSEA = 0.065 (90% CI: 0.046-0.083), and PCLOSE = 0.087.

The standardized factor loading magnitudes for all 15 items were satisfactory (above 0.60), with all p-values below 0.001. Specifically, the loading values for the resource factor ranged from 0.766 to 0.928, for the challenge factor from 0.699 to 0.891, and for the hindrance factor from 0.602 to 0.847. The AVE exceeded 0.50 in all cases, corresponding to 0.722 for the resource factor, 0.703 for the challenge factor, and 0.598 for the hindrance factor. Convergent validity was thus ensured. Discriminant validity was confirmed as well, given that the square root of AVE for each construct was higher than the correlation coefficients between the focal factor and all the other factors (the correlation coefficients ranged from 0.040 to 0.731). The CR score for each of the AIRA appraisal subscale was greater than the threshold value of 0.70, attaining 0.928 for the resource factor, 0.922 for the challenge factor, and 0.880 for the hindrance factor, which indicate good construct reliability (Table 3).

Table 3.
Confirmatory factor analysis results – validation subsample (N = 184)

Factor/item	Mean	Std Dev	Skewness	Kurtosis	Factor loading	CR	AVE
AIRA-Resource						0.928	0.722
AIRA2	4.39	1.503	-0.319	-0.080	0.796		
AIRA3	4.18	1.454	-0.220	-0.220	0.836		
AIRA4	4.24	1.510	-0.423	-0.111	0.766		
AIRA5	3,92	1.592	-0.087	-0.428	0.912		
AIRA6	4.05	1.562	-0.291	-0.364	0.928		
AIRA-Challenge						0.922	0.703
AIRA7	3.99	1.441	-0.424	0.012	0.824		
AIRA8	3.99	1.519	-0.275	-0.278	0.877		
AIRA9	3.85	1.604	-0.175	-0.472	0.887		
AIRA11	3.91	1.583	-0.282	-0.550	0.891		
AIRA12	3.80	1.641	-0.177	-0.538	0.699		
AIRA-Hindrance						0.880	0.598
AIRA13	3.32	1.749	0.161	-0.998	0.798		
AIRA14	3.16	1.684	0.358	-0,751	0.801		
AIRA15	3.33	1.677	0.258	-0.663	0.847		
AIRA16	3.24	1.626	0.284	-0.631	0.796		
AIRA18	4.22	1.681	-0.334	-0.520	0.602		

Note: All factor loadings are significant at $p < 0.001$.

The goodness of fit of the proposed model was compared against three other models: model A, in which all 15 items loaded onto one factor; model B, in which 10 items loaded onto the resource-challenge factor and 5 items onto the hindrance factor; and model C, in which 5 items loaded onto the resource factor and 10 items onto the challenge-hindrance factor. The proposed model provided a better fit to the data than alternative ones, as indicated by lower values of χ^2/df, SRMR, RMSEA, AIC, and BIC, and higher values of CFI, TLI, IFI, and PCLOSE (Table 4).

Table 4.
Fit indices for the proposed model and alternative models – validation subsample (N = 184)

Model	χ^2/df	CFI	TLI	IFI	SRMR	RMSEA	PCLOSE	AIC	BIC
Base model – three factors	1.780	0.974	0.961	0.974	0.053	0.065	0.087	224.16	378.48
Model A – one factor	10.003	0.618	0.555	0.621	0.187	0.222	0,000	960.28	1056.73
Model B – two factors	4.721	0.844	0.816	0.845	0.075	0.143	0.000	428.21	581.87
Model C – two factors	7.985	0.707	0.655	0.709	0.180	0.195	0.000	772.67	872.33

Note: In model B resource and challenge appraisals were combined, in model C challenge and hindrance appraisals were combined.

In summary, the results of the EFA and CFA indicate that the AIRA appraisal scale presents an adequate fit with the observed data and demonstrates sufficient reliability and validity.

4.3. Variations in the AIRA appraisals

To examine whether the AIRA appraisals differ by dimension and employee subgroup, we analyzed the summated scales, which were created by averaging the scores of the items measuring each construct. The descriptive statistics indicate that AIRA in the workplace is primarily perceived by employees as a resource, followed by a challenge, and lastly as a hindrance (Table 5).

Table 5.
Descriptive statistics and correlations – full sample (N = 369)

Variable	Mean	Std Dev	Skewness	Kurtosis	Correlations		
					1	2	3
AIRA-Resource	4.22	1.305	-0.306	0.208	---		
AIRA-Challenge	4.01	1.255	-0.404	0.395	0.735^{***}	---	
AIRA-Hindrance	3.49	1.373	0.124	-0.458	-0.008	0.073	---

Note: Significant at * p < 0.05; ** p < 0.01; *** p < 0.001 (two-tailed).

A one-way repeated measures analysis of variance with a Greenhouse-Geisser correction showed a statistically significant difference among the employees' appraisals toward AIRA ($F(1.385,509.552) = 40.506$, $p < 0.001$, $\eta_p^2 = 0.099$). Post-hoc comparisons with Bonferroni corrections revealed significant pair-wise differences between resource and challenge appraisals, with a mean difference of 0.210 ($p < 0.001$), between resource and hindrance appraisals, with a mean difference of 0.729 ($p < 0.001$), and between challenge and hindrance appraisals, with a mean difference of 0.519 ($p < 0.001$).

The findings of a series of independent-samples t-tests demonstrate that the variations in how diverse subgroups of employees appraised AIRA in the workplace are predominantly attributable to the respondents' overall digital competences and AIRA knowledge. Individuals who self-identify as more tech-savvy and well-informed about AIRA tend to regard AIRA as both a resource and a challenge more frequently than their colleagues. Notably, ratings concerning the perception of AIRA as a hindrance remained unaffected by these features (Table 6).

Table 6.
Variations in the appraisals – full sample (N = 369)

Variable	AIRA-Resource	AIRA-Challenge	AIRA-Hindrance
Female	4.15 (1.248)	3.95 (1.197)	3.50 (1.387)
Male	4.36 (1.400)	4.13 (1.356)	3.49 (1.352)
t-value	-1.445	-1.244	0.022
30 years old or younger	4.26 (1.273)	4.00 (1.223)	3.57 (1.422)
Over 30 years old	4.20 (1.329)	4.03 (1.280)	3.44 (1.338)
t-value	0.472	-0.208	0.859
Tertiary	4.35 (1.231)	4.09 (1.163)	3.47 (1.356)
Secondary or lower	4.08 (1.370)	3.93 (1.347)	3.52 (1.395)
t-value	2.015*	1.229	-0.326
Managerial	4.32 (1.405)	4.21 (1.391)	3.42 (1.423)
Non-managerial	4.18 (1.255)	3.92 (1.178)	3.53 (1.351)
t-value	0.997	2.090*	-0.693
Permanent contract	4.15 (1.301)	4.00 (1.264)	3.63 (1.288)
Non-permanent contract	4.30 (1.308)	4.02 (1.250)	3.35 (1.446)
t-value	-1.084	-0.145	1.924
Less than 50 employees	4.21 (1.346)	3.98 (1.276)	3.46 (1.465)
50 employees or more	4.26 (1.227)	4.08 (1.217)	3.57 (1.177)
t-value	-0.341	-0.742	-0.780
Accommodation, food and beverages	4.19 (1.324)	4.01 (1.313)	3.52 (1.415)
Recreation, entertainment, arts	4.27 (1.280)	4.01 (1.173)	3.46 (1.315)
t-value	-0.553	-0.011	0.402
High AIRA knowledge	4.69 (1.422)	4.51 (1.246)	3.32 (1.399)
Low AIRA knowledge	4.04 (1.208)	3.82 (1.206)	3.56 (1.359)
t-value	4.156***	4_926***	-1.524
High digital competences	4.44 (1.301)	4.22 (1.250)	3.49 (1.444)
Low digital competences	3.84 (1.225)	3.64 (1.180)	3.50 (1.243)
t-value	4.366***	4.352***	-0.054

Note: Values in parentheses are standard deviations. Significant at * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed).

5. Discussion

There is a broad consensus that intelligent technologies are increasingly reshaping service industries, causing a profound transformation in how organizations function (Huang, Rust, 2018). As AIRA becomes more pervasive in organizational operations, service employees, among other stakeholders, are directly influenced by its adoption. The present study was designed to provide insights into employees' appraisals toward AIRA in the workplace in service environments. To this end, we developed and validated the AIRA appraisal scale, which consists of three subscales: resource appraisal toward AIRA, challenge appraisal toward AIRA, and hindrance appraisal toward AIRA.

A key contribution of this work to the existing body of knowledge lies in offering of a more comprehensive and nuanced view of how employees perceive AIRA adoption into service organizations. First, our investigation lends further credence to the refined classification of job characteristics in the JD-R model proposed by Crawford, LePine, and Rich (2010). Specifically, the study's results provided support for the differentiation between the three appraisals categories. Both the explanatory and confirmatory stages of the analysis led to the conclusion that a tripartite solution presented an adequate fit with the observed data. Furthermore, confirmatory analysis revealed that the fit of an alternative two-factor structure, consistent with the original JD-R model, was inferior compared to the three-factor one.

Second, distinct from previous research grounded in the JD-R model, we refrained from making *a priori* categorizations of individuals' appraisals of workplace conditions. Instead, based on the premise that appraisals are functions of a specific set of environmental conditions and characteristics of the person engaged in the appraising process (Lazarus, Folkman, 1984), we opted to measure directly employees' appraisals of AIRA-driven work circumstances. In this regard, our position aligns with that of Webster, Beehr, and Love (2011) and Searle and Auton (2015), who argue that it is the appraisals that serve as the underlying mechanism linking workplace situations to outcomes and that situations may not be appraised consistently by different individuals and across different settings.

Third, unlike the majority of the prior empirical work that addressed AIRA's effects on work experiences and outcomes, our study does not ascertain that the implementation of AIRA is exclusively a job demand producing work stress. We propose that a scenario in which AIRA adoption is recognized as a circumstance exceeding employees' resources and requiring coping efforts is an option, not a certainty. In fact, our results indicated that employees perceive AIRA in the workplace mostly as a resource and least as a hindrance. This finding resonates to some extent with the theory of AI job replacement put forth by Huang and Rust (2018). This theory is based on the four intelligences framework (mechanical, analytical, intuitive, and empathetic) and asserts that AI job replacement occurs essentially at the task level, with mechanical tasks being replaced first, followed by analytical tasks, intuitive tasks, and empathetic tasks. Service jobs requiring frequent and extensive interactions with customers are less prone to the replacement by AIRA due to their heavy reliance on intuitive and empathetic intelligence. Tasks involving intuitive and empathetic skills are more difficult to be mimicked by intelligent technology because they require holistic and contextual understanding, along with a high level of social and emotional presence (Huang, Rust, 2018). In summary, when successful service provision demands a strong human touch, AIRA contributes predominantly to job augmentation rather than replacement, thereby being perceived as a facilitating rather than threatening work circumstance.

The findings of this study offer practical implications for service industry businesses. Given the multifaceted impact of AIRA on performance, with varying pathways in play, it is crucial for managers to understand employees' appraisals toward AIRA in the workplace. Indeed, the appraisals of work circumstances rather than work circumstances themselves have a critical implication for employees' attitudinal and behavioral responses. Depending on appraisals, AIRA integration into organizational operations has the potential to be a double-edged sword. On the one hand, it can be a motivational force, leading to favorable outcomes; on the other hand, it can be a strain-related experience, resulting in unfavorable outcomes. By understanding appraisals, managers can take targeted actions to enhance the motivation pathway and mitigate the strain pathway. These actions can assist service organizations in formulating and implementing effective strategies and practices for the adoption of intelligent technologies.

The study demonstrated that individuals who perceive themselves as more technologically adept and more knowledgeable about AIRA are more inclined to regard AIRA as a resource compared to their colleagues. Hence, a strongly recommended initiative employers could consider is investing in supporting their employees' digital competencies. Specifically, organizations should implement training programs designed to enhance employees' knowledge and skills on digital technologies in general and intelligent technologies in particular. Also, training programs focused on developing intuitive and empathetic skills are highly advised, as these skills are more difficult for intelligent technology to replicate. Such programs equip employees with personal resources that can be utilized to counteract the demands imposed by challenging or threatening work circumstances, thereby mitigating the potential negative effects of AIRA implementation.

The present study was conducted with meticulous attention to rigor; nevertheless, several limitations merit consideration. First, we relied on single-source data and the variable of interest was based on self-reported measures. Hence, there is a possibility for common method bias to occur, particularly the response consistency effect. In future studies, data collection should be expanded to include multiple sources to shed more light on the constructs under investigation. Second, we employed a non-probability sampling technique and an online survey to gather data, which may have resulted in a biased sample. Furthermore, the questionnaire was disseminated among employees of selected service industries in Poland. This restriction limits the generalizability of the findings beyond the specific context of this research. Therefore, replication studies are required to ascertain whether the results of the present research are industry- and country-specific or universally observed in service organizations. Finally, we focused exclusively on employees' appraisals toward AIRA, but did not account for the work-related antecedents and effects of these appraisals. Consequently, it is recommended that future studies investigate more complex linkages covering both driving and outcome variables. Particularly, it would be of value to examine organizational determinants of AIRA adoption perceptions and its impact on job performance, including the role of mediators along motivation and strain pathways. Such an examination could result in an enriched understanding of the mechanisms through which AIRA appraisals influence service employee performance.

6. Summary

Despite the growing body of research examining the links between AIRA adoption and work-related outcomes, studies that employ individual-level analysis remain underrepresented (Pereira et al., 2023). The present study aims to address this gap by enhancing the understanding of employees' appraisals toward AIRA in the workplace in service settings. The primary contribution of our investigation is to provide a comprehensive and nuanced perspective on employees' perceptions of AIRA integration into service delivery processes. The proposed perspective is better suited to explain employees' attitudinal and behavioral reactions to the changing work environment driven by AIRA, which is crucial for developing strategies to successfully integrate intelligent technologies within service organizations.

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Appendix

Table 7.
Item symbols and item descriptions

Item symbol	Item
AIRA1*	AIRA will take over mundane tasks from me at work.
AIRA2	AIRA will eliminate a lot of repetitive and tedious work for me.
AIRA3	Thanks to AIRA, I will be able to focus on more rewarding tasks at work.
AIRA4	AIRA will reduce workload for me.
AIRA5	AIRA will give me more freedom to decide how to go about doing the work.
AIRA6	Thanks to AIRA, I will perform my job duties more efficiently.
AIRA7	The job challenges generated by AIRA will help me to learn a lot.
AIRA8	AIRA will exert pressure on me to develop my skills.
AIRA9	The job challenges generated by AIRA will allow me to use a broad set of skills and abilities at work.
AIRA10*	Despite challenges, AIRA will support my professional achievements.
AIRA11	AIRA will require me to focus on more complex tasks at work.
AIRA12	AIRA will increase my job responsibilities.
AIRA13	I am personally worried that what I do now in my job will be able to be replaced by AIRA.
AIRA14	I am quite pessimistic about my future in this industry because employees could be replaced with AIRA.
AIRA15	AIRA will hinder any professional achievements I might have.
AIRA16	AIRA will result in job demands that will be too much for me to handle.
AIRA17*	AIRA will worsen interpersonal relations at work.
AIRA18	AIRA will one day make human employees obsolete.

Note: Items with * were dropped during EFA.