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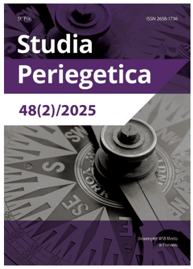

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Appraisals Matter: How Artificial Intelligence, Robotics, and Automation Affect Tourism Employees' Service Performance

Abstract. Organisations worldwide are undergoing a profound technological transformation driven by advances in artificial intelligence, robotics, and automation (AIRA). AIRA technologies are reshaping not only their structural and operational foundations but also the nature of human work. Drawing on the job demands–resources (JD-R) model, the author examines how tourism employees' appraisals of AIRA relate to their service performance, which is a key factor of competitive advantage and the long-term success of tourism organisations. The analysis presented in the article is based on quantitative data collected in an online survey involving 303 tourism employees in Poland. Hierarchical multiple regression analysis and the PROCESS macro were used to test the hypotheses. Results reveal the dual nature of AIRA appraisals: demand appraisals undermine service performance by increasing job burnout, whereas resource appraisals enhance performance by fostering job engagement. These findings highlight the importance of human-centred strategies in digital transformation in tourism, ensuring that AIRA technologies support rather than replace human contribution.

Keywords: artificial intelligence, robotics and automation (AIRA), workplace, appraisal, service performance, tourism

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1. Introduction

There is broad consensus among scholars and practitioners that organisations worldwide are undergoing a profound technological transformation driven by the rapid development of smart technologies (Borges et al., 2021; Bankins et al., 2024),

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particularly artificial intelligence, robotics, and automation (AIRA). This transformation is especially evident in the tourism sector, where technological innovations increasingly substitute or complement human labour in service delivery (Buhalis et al., 2019; Tussyadiah, 2020). Although services have traditionally been regarded as difficult to automate due to their reliance on contextual understanding and spontaneous interpersonal communication (Huang & Rust, 2018), recent advances in AIRA are reshaping how service work is organised and performed. In tourism, these technologies are being adopted to reduce costs, enhance efficiency, increase productivity, and enrich customer experiences through data-driven personalisation and process optimisation (Buhalis et al., 2019; Lu et al., 2020). Consequently, AIRA technologies are not only transforming the structural and operational foundations of tourism organisations but also redefining the nature of human work.

The current discourse on the integration of AIRA within organisational contexts remains highly fragmented (Lu et al., 2020; Pereira et al., 2023). This fragmentation stems from the complex and multidimensional nature of AIRA implementation, which involves a broad spectrum of stakeholders, each with distinct implications resulting from the integration process. While smart technologies create unique opportunities for improving business capabilities, their adoption is often accompanied by substantial challenges and internal tensions (Benbya, Pachidi, & Jarvenpaa, 2021). As a result, many organisations struggle to align their social systems with the rapid evolution of technical systems (Yu, Xu, & Ashton, 2023). In the tourism industry, where human interaction and service quality are central to organisational success, this struggle is particularly challenging. The effective implementation of AIRA therefore requires an integrated approach that accounts for the development of social and technical dimensions (Bélanger, Watson-Manheim, & Swan, 2013). In this context, attitudes towards technological change are of critical importance, as they largely determine to what extent employees are willing to adopt AIRA-enabled solutions and, ultimately, affect the success of such implementations (Yu, Xu, & Ashton, 2023). Consequently, to better understand the mechanisms underlying the successful integration of AIRA into tourism organisations, research attention should shift from the mere exposure to smart technologies to the way these technologies are appraised by employees (Salanova & Schaufeli, 2000).

Although research on the role of AIRA in service business settings has grown considerably in recent years, several gaps remain in the current body of knowledge. Firstly, despite notable progress in understanding technology acceptance, the integration of AIRA into service production and delivery processes has been examined predominantly from the organisational perspective, with comparatively less attention paid to the role of employees (Lu et al., 2020; Pereira et al., 2023). This is a critical omission, as employees play a central role in the success of smart transformation initiatives, and understanding their perceptions and attitudes towards technological change is essential for ensuring effective outcomes. Secondly, studies of employees' perceptions of smart technologies have largely conceptualised AIRA implementation as a job demand that generates work stress (Liang et al., 2022; Bednarska & Łuka, 2025). Consequently, research has tended to emphasise the detrimental effects of AIRA on work-related experiences and outcomes. The present study challenges this one-sided view by acknowledging that while AIRA adoption can be experienced as a job demand involving coping efforts and certain costs, it can also be interpreted as a job resource enhancing work motivation and employee performance.

Building on this premise, the following study did not make any *a priori* assumptions about how employees perceive AIRA in their workplace. Instead, it follows the view that such appraisals constitute the underlying mechanism linking workplace conditions to employee outcomes, and that the same situation may not be appraised consistently by different individuals and across different settings (Webster, Beehr, & Love, 2011). Accordingly, the purpose of this study was to investigate the relationships between tourism employees' appraisals of AIRA in the workplace and their service performance.

The remainder of the paper is structured as follows. The next section reviews the relevant literature and presents the research model developed on the basis of this review. The subsequent sections describe the research method and report the results of the study, which are followed by a discussion of the main findings. The article ends with a list of study limitations and suggested directions for future research.

2. Theoretical Background and Research Hypotheses

The rapid and continuous advances in smart technologies, AIRA in particular, have precipitated substantial changes in the employment landscape across industries, manifesting in both structural and content-related dimensions. At the structural level, technological innovations have reshaped the composition and organisation of the labour market, while at the content level, they have transformed the nature of tasks and the demands faced by employees (Trenerry et al., 2021; Toscanelli, Udayar, & Massoudi, 2022). These developments have also affected service industries, which have conventionally been considered to be less susceptible to digital transformation as they entail heterogeneous contextual understanding and interaction (Huang & Rust, 2018). Indeed, in the contemporary environment, AIRA technologies have been shown to profoundly and increasingly alter the nature of service jobs and service workplace relations (Noble et al., 2022; Vorobeva et al., 2022).

While the use of digital technologies by organisations as a strategic tool is not a novel practice, the adoption of smart technologies is becoming considerably more intricate, since AIRA-enabled applications are capable of performing tasks that require cognition formerly exclusively associated with humans (Benbya, Pachidi, & Jarvenpaa, 2021; Borges et al., 2021). The extent to which developments in these technologies have the potential to impact service workplaces can be elucidated by the theory of AI job replacement proposed by Huang and Rust (2018). This theory, which is based on the four types of intelligence (mechanical, analytical, intuitive, and empathetic) posits that AI job replacement occurs essentially at the task level, starting with mechanical tasks and moving towards empathetic ones. Tasks involving mechanical and analytical skills — such as greeting customers, data entry, reservation processing, or responding to structured customer inquiries — are easier to be imitated by AIRA, because they predominantly depend on maintaining precision and consistency, or systematic and rule-based learning. Conversely, tasks involving intuitive and empathetic skills — such as tailoring service to nuanced guest preferences, handling contextual customer requests, resolving emotionally charged customer complaints, or reading social cues — are more difficult to be mimicked by AIRA because they necessitate holistic and contextual understanding, along with a high level of social and emotional presence (Huang & Rust, 2018).

Research on the use of AIRA in service settings reveals that service tasks vary markedly in their susceptibility to automation. In the emerging feeling economy, tasks that call for empathy, nuanced social understanding, and intensive interpersonal exchanges remain the least replaceable because they rely on feeling intelligence (Huang, Rust, & Maksimovic, 2019; Huang & Rust, 2021). Tourism service encounters typically involve high-touch, relational interactions and require employees to respond sensitively to guests' emotions and expectations. These characteristics help explain why employees performing such tasks may appraise AIRA differently from those whose roles encompass more routine or analytical tasks. The emotional and relational nature of tourism services thus provides an important lens for interpreting employees' appraisal patterns and their implications for service performance.

The introduction of AIRA technologies into workplaces has generated an intense debate about their implications for employees, with opinions divided between optimistic and pessimistic views. This polarisation can be explained by the automation–augmentation paradox (Raisch & Krakowski, 2021). The automation perspective suggests that machines take over human tasks, which results in the replacement of human labour, i.e. a decline in job quantity. In contrast, the augmentation perspective assumes that humans collaborate closely with machines to perform tasks, which contributes to enhanced job quality (Gmyrek, Berg, & Bescond, 2023). In tourism contexts, both dynamics are visible: AIRA can automate routine operations as well as augment human employees' ability to deliver more consistent, personalised, and creative service experiences.

Empirical studies provide evidence supporting both sides of this paradox. Some research has recognised that the implementation of AIRA has the potential to improve employee well-being. This is achieved by reducing routine, repetitive, and mundane tasks, thereby minimizing fatigue and enabling more rewarding activities and meaningful work (Qiu et al., 2022; Kassa & Worku, 2025). Conversely, other studies have demonstrated that as AIRA applications encroach upon roles once considered to be unsuitable for algorithmisation, they may potentially send the signal to employees that their jobs are at risk. This could cause employees to feel undervalued and unappreciated by their organisations and result in an increased perception of job insecurity (Brougham & Haar, 2018; Sharif et al., 2025). Furthermore, rapid AIRA-induced changes in work environment have been shown to create an atmosphere of unpredictability, which is associated with higher stress and burnout levels (Toscanelli, Udayar, & Massoudi, 2022; Zheng et al., 2025). Additionally, researchers have observed that the presence of AIRA may result in employees competing against one another for recognition, thereby contributing to knowledge hiding and deterioration of workplace relationships (Li, Bonn, & Ye, 2019; Arias-Pérez & Vélez-Jaramillo, 2022). Last but not least, the adoption of AIRA in the workplace, owing to its disruptive capacity, has been demonstrated to hinder employees' organisational commitment and encourage job mobility (Kong et al., 2021; Zhang & Jin, 2023).

A relevant framework for conceptualizing how appraisals of AIRA affect work outcomes is the job demands–resources (JD-R) model (Demerouti et al., 2001). The JD-R model is a unifying job design model that elucidates the mechanisms by which individuals' workplace attitudes and behaviours 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 organisational aspects of the job that require sustained physical, cognitive, and emotional effort and are associated with certain physiological and psychological costs. Job resources in turn refer to the physical, psychological, social, or organisational aspects of the job that help to achieve work-related goals, stimulate personal growth and development, and reduce job demands and the associated physiological and psychological costs (Demerouti et al., 2001).

According to the model, 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 behaviours, yielding opposite effects on work-related outcomes (Demerouti et al., 2001). The strain process is initiated by job demands, because the increased effort of having to cope with demands results in resource depletion, which may lead to job burnout. The motivation process is initiated by job resources, as they facilitate the achievement of valued goals and thereby may enhance job engagement. Work-related strain has been shown to contribute to unfavourable work-related outcomes by diverting employees from work goals; in contrast, work-related motivation has been demonstrated to add to favourable work-related outcomes by facilitating the adoption of goal-oriented behaviours (Bakker & Demerouti, 2017).

Importantly, specific work circumstances may not be uniformly appraised by employees, as such appraisals are shaped by the interplay between contextual conditions and individual characteristics. Consistent with cognitive appraisal theory (Lazarus & Folkman, 1984), employees interpret workplace situations by assessing whether an encounter with the environment is relevant to their well-being and, if so, whether it signals potential gains or losses. Individual appraisals therefore not only reflect how employees evaluate prospective advantages or disadvantages associated with a situation, but also their perceived capacity to respond to it (Ding, 2021). Furthermore, different appraisals are not mutually exclusive; a workplace situation may be, to varying degrees, perceived in more than one way (Webster, Beehr, & Love, 2011). Therefore, using predetermined categorisations of appraisals is deemed an invalid approach, as it does not accurately reflect employees' perceptions. Ultimately, it is the way situations are appraised, not the situations themselves, that explains employees' attitudinal and behavioural reactions. This is why it is posited that tourism employees may appraise the implementation of AIRA in the workplace as a demanding or facilitating work circumstance. On the one hand, the adoption of AIRA in tourism service delivery processes may be construed as a job demand on account of its capacity to evoke employees' fears of job replacement (Brougham & Haar, 2018), which leads to an increased sense of job insecurity (Huang & Gursoy, 2024) and triggers workplace anxiety (Liu et al., 2024). On the other hand, it may also be perceived as a job resource, because AIRA technologies can enhance employees' efficiency and effectiveness in work roles (Marinova et al., 2017) by eliminating some of the mundane and tedious tasks (Kassa & Worku, 2025) and facilitating creative problem-solving (Jia et al., 2024) ultimately assisting in the delivery of high-quality experiences.

In summary, AIRA technologies constitute a double-edged sword, which can potentially induce job burnout that undermines desirable work-related outcomes while simultaneously fostering job engagement that enhances them. In the context of tourism, service performance is a particularly relevant work-related outcome, which is defined as a behavioural manifestation of employees' capacity to effectively address customer needs (Liao & Chuang, 2004). Behaviours of service providers are widely acknowledged as a critical determinant of customer outcomes, which, in turn, represent key drivers of organisational performance (Bettencourt & Brown, 2003; Bowen & Schneider, 2014). As such, service performance is fundamental to maintaining competitive advantage and ensuring the long-term success of tourism organisations. It is therefore important, for theoretical and practical reasons, to understand its relationship with employees' appraisals of AIRA in the workplace.

Given the theoretical and empirical insights described above, it is assumed that employees' appraisals of AIRA in the workplace play a pivotal role in shaping their performance. Specifically, service performance is expected to depend on whether AIRA technologies are construed as job demands or job resources (hereafter referred to as demand appraisals of AIRA and resource appraisals of AIRA, respectively). Accordingly, the following hypotheses are proposed (Fig. 1):

H1: Demand appraisals of AIRA are negatively associated with service performance.

H2: Resource appraisals of AIRA are positively associated with service performance.

H3: Job burnout mediates the negative relationship between demand appraisals of AIRA and service performance.

H4: Job engagement mediates the positive relationship between resource appraisals of AIRA and service performance.

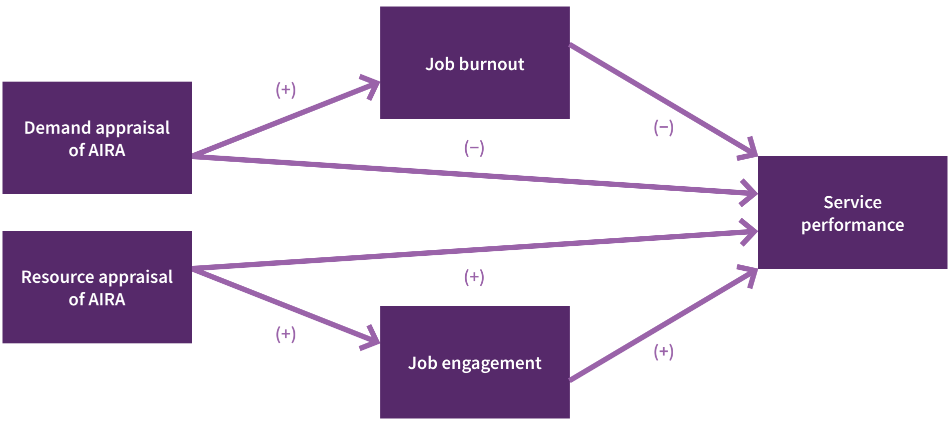

Fig. 1. Proposed research model
Source: Author

3. Methods

The target population for the present study comprised individuals employed in the tourism industry in Poland. Specifically, respondents were recruited from the accommodation, food and beverage, recreation, entertainment, and arts sectors. Data were collected through an online survey administered by an external company, Ariadna, the largest independent nationwide research panel in Poland. Ariadna is recognised for its adherence to rigorous scientific standards and ethical research practices.

Data collection took place in August 2024. Respondents were recruited using a non-probability voluntary response sampling technique. A total of 458 individuals volunteered to participate in the study and met the inclusion criteria concerning their industry of employment and experience with using AIRA at work. After excluding 155 cases owing to incorrect responses to the attention check question (n=98), extremely short completion time (n=23), and implausible response patterns (n=34), the final sample consisted of 303 respondents (Table 1).

Table 1. Respondent profiles

Variable	Category	N	%
Sex	Female	196	64.7
	Male	107	35.3
Age	20 years old or younger	20	6.6
	21–30 years old	107	35.3
	31–40 years old	95	31.4
	41–50 years old	59	19.5
	Over 50 years old	22	7.3
Education	Tertiary	160	52.8
	Secondary	127	41.9
	Vocational	14	4.6
	Primary	2	0.7
Job position	Managerial	100	33.0
	Non-managerial	203	67.0
Employment contract	Permanent contract	155	51.2
	Fixed-term contract	50	16.5
	Self-employment	28	9.2
	Mandate contract/ contract for specific work	60	19.8
	Other	10	3.3
Job tenure in current workplace	Up to 3 months	32	10.6
	Over 3 months to 1 year	46	15.2
	Over 1 year to 3 years	78	25.7
	Over 3 years to 5 years	53	17.5
	Over 5 years to 10 years	55	18.2
	Over 10 years	39	12.9
Company size	Less than 10 employees	79	26.1
	10–49 employees	119	39.3
	50–249 employees	72	23.8
	Over 249 employees	33	10.9

Variable	Category	N	%
Type of economic activity	Accommodation, food and beverages sector Recreation, entertainment, and arts sector	175 128	57.8 42.2

Source: Author

The questionnaire used in this study consisted of three sections. The first section was designed to elicit participants' opinions about the consequences of implementing AIRA in the workplace. The second section contained statements regarding selected employee attitudes and behaviours, while the third one collected socio-demographic and job-related information. For all items in the first and second sections, participants indicated their level of agreement with each statement on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

All measurement scales related to employees' appraisals, attitudes, and behaviours were adapted from established instruments in the literature. Because the scales were originally developed in English, the standard back-translation procedure was used to ensure the linguistic and conceptual equivalence of the Polish version. In addition, a pre-test was conducted to verify the relevance, clarity, and comprehensiveness of the questions and response options. Ten individuals representing the target population completed the questionnaire and provided feedback on its content. The pre-test revealed no major issues regarding item wording or comprehension.

Appraisal of AIRA as a demand was measured using five items derived from Brougham and Haar (2018) and Ding (2021). Example items include: "I am quite pessimistic about my future in this industry because employees could be replaced with AIRA" and "AIRA will hinder any professional achievements I might have." The Cronbach's alpha coefficient for this scale was 0.861. Appraisal of AIRA as a resource was measured using five items developed by Bednarska and Łuka (2025). Example items include: "AIRA will eliminate a lot of repetitive and tedious work for me" and "Thanks to AIRA, I will perform my job duties more efficiently." The Cronbach's alpha coefficient for this scale was 0.884. Job burnout was measured using six items adapted from the shortened version of the burnout scale originally developed by Schaufeli, Desart, and De Witte (2020) and further refined by Hadžibajramović, Schaufeli, and De Witte (2024). Example items include: "At work, I feel mentally exhausted" and "I struggle to find any enthusiasm for my work." The Cronbach's alpha coefficient for this scale was 0.850. Job engagement was measured using six items adapted from the shortened version of the engagement scale originally developed by Rich, LePine, and Crawford (2010) and later refined by Houle et al. (2022). Example items include: "I exert my full effort to my job" and "At work, I focus a great deal of attention on my job." The Cronbach's alpha coefficient for this scale was 0.916. Service performance was measured using six items derived from Bettencourt, Gwinner, and Meuter (2001) and Liao and Chuang (2004). Example items include: "I follow customer service guidelines with extreme care" and "Regardless of circumstances, I am courteous and respectful to customers." The Cronbach's alpha coefficient for this scale was 0.944.

The statistical processing of the survey data began with descriptive statistics and correlation analysis to examine the basic characteristics of the variables of interest and the associations between them. To test the proposed hypotheses, two sets of analyses were performed. Firstly, hierarchical multiple regression was used to investigate the relationships between the dependent and mediating variables and their antecedents. Secondly, the PROCESS macro, a tool for path analysis, was used to assess the mediating effects in the research model. All statistical procedures were carried out using SPSS software. The use of regression and mediation analyses makes it possible to examine direct and indirect effects of employees' appraisals of AIRA on service performance, thus enables operationalisation of the relationships suggested by the model. This approach is consistent with the JD-R framework, which posits that job demands and resources influence work outcomes through employee well-being.

4. Results

Prior to testing the empirical model, the means, standard deviations, and correlations among all key study variables were computed (Table 2). As shown, tourism employees were less likely to appraise AIRA as a job demand than as a job resource ($M=3.53$, $SD=1.25$ vs. $M=4.52$, $SD=1.06$), and correlations between both appraisals were weak and nonsignificant ($r=-0.06$, $p=0.324$). As expected, demand appraisals of AIRA were significantly and positively associated with job burnout ($r=0.33$, $p<0.001$) and significantly and negatively associated with job engagement ($r=-0.21$, $p<0.001$) and service performance ($r=-0.21$, $p<0.001$). In contrast, resource appraisals of AIRA were significantly and negatively related to job burnout ($r=-0.17$, $p=0.002$) and significantly and positively related to job engagement ($r=0.33$, $p<0.001$) and service performance ($r=0.23$, $p<0.001$). Finally, service performance was significantly and negatively correlated with job burnout ($r=-0.36$, $p<0.001$) and significantly and positively correlated with job engagement ($r=0.76$, $p<0.001$). These results provide preliminary support for the hypothesised links.

Table 2. Descriptive statistics and correlations for the study variables

Variable	M	SD	Correlations			
			1.	2.	3.	4.
1. D–AIRA	3.529	1.248				
2. R–AIRA	4.524	1.064	−0.057			
3. Job burnout	3.468	1.234	0.330***	−0.175**		
4. Job engagement	5.309	1.128	−0.213***	0.325***	−0.439***	
5. Service performance	5.674	1.113	−0.208***	0.234***	−0.362***	0.764***

M — mean, SD — standard deviation, D–AIRA — demand appraisal of AIRA; R–AIRA — resource appraisal of AIRA
Significant at * p<0.05; ** p<0.01; *** p<0.001 (2-tailed)
Source: Author

To examine the effects of AIRA appraisals on service performance, a series of hierarchical regression models was estimated (Table 3). Specifically, job burnout and job engagement were regressed on demand and resource appraisals of AIRA, respectively, while service performance was regressed on both appraisals of AIRA and on job burnout and job engagement. All models controlled for the potentially confounding effects of respondents' sex, age, education, job position, and job tenure.

As shown in model 6, demand appraisals of AIRA were a significant negative predictor of service performance ($\beta=-0.18$, $p<0.01$), whereas resource appraisals of AIRA were a significant positive predictor of service performance ($\beta=0.22$, $p<0.001$), after controlling for socio-demographic and job-related variables. Thus, hypotheses 1 and 2 found support in the data. As demonstrated in models 7 and 8, when job burnout and job engagement were added to the regression equation, the direct effects of both appraisals of AIRA on service performance became smaller. Moreover, as indicated in models 2 and 4, demand and resource appraisals of AIRA significantly contributed to job burnout and job engagement, respectively. This pattern suggests that job burnout and job engagement may mediate the relationships investigated in the study.

Table 3. Results of regression analysis

	Job burnout		Job engagement		Service performance			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Control variables								
Sex	0.001	−0.012	0.033	0.011	−0.087	−0.095	−0.095	−0.110**
Age	−0.086	−0.050	0.136*	0.114	0.143*	0.107	0.095	0.035
Education	0.082	0.035	−0.049	−0.030	−0.039	0.001	0.009	0.003
Job position	−0.045	−0.055	−0.104	−0.082	−0.055	−0.034	−0.054	0.025
Job tenure	0.117	0.078	−0.091	−0.044	−0.073	−0.017	0.000	0.000
Independent variables								
D–AIRA		0.321***				−0.180**	−0.086	−0.039
R–AIRA				0.312***		0.225***	0.178**	−0.008

	Job burnout		Job engagement		Service performance			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mediating variables								
Job burnout							−0.301***	
Job engagement								0.763***
R^2	0.018	0.117	0.032	0.127***	0.028	0.112***	0.189***	0.600***
ΔR^2		0.099***		0.095***		0.084***	0.078***	0.498***
F	1.076	6.531***	1.975	7.176***	1.706	5.296***	8.580***	55.176***

Reference categories: sex — female, age — 20 years old or younger, education — tertiary, job position — managerial, job tenure — less than 3 months
Standardised coefficients are provided.
Significant at * p<0.05; ** p<0.01; ***p<0.001
Source: Author

In line with Hayes's (2022) recommendations, mediation analyses were conducted using the PROCESS macro (model 4) to examine the indirect effects of AIRA appraisals on service performance via job burnout and job engagement. The effects were tested using a bootstrapping resampling procedure with 5000 iterations and bias-corrected bootstrap estimates to generate 95% confidence intervals (Table 4).

The analysis revealed a significant indirect effect of demand appraisals of AIRA on service performance through job burnout (indirect effect =−0.10, SE=0.03, 95% CI [−0.15, −0.05]). Higher levels of demand appraisals were associated with greater job burnout, which in turn predicted lower service performance. The direct effect of demand appraisals on service performance was nonsignificant (β=−0.09, SE=0.06, 95% CI [−0.20, 0.03]), suggesting full mediation through job burnout. Thus, hypothesis 3 was supported. The indirect effect of resource appraisals of AIRA on service performance via job engagement was also found to be statistically significant (indirect effect =0.23, SE=0.05, 95% CI [0.14, 0.33]). Employees who appraised AIRA as a resource reported higher levels of job engagement, which subsequently enhanced their service performance. The direct effect of resource appraisals on service performance was nonsignificant (β=−0.01, SE=0.04, 95% CI [−0.09, 0.07]), indicating that their effect on performance was fully mediated by job engagement. Therefore, hypothesis 4 was also supported.

Table 4. Results of mediation analysis

Paths	Effects	Coefficients	SE	95% CI LL	95% CI UL
D–AIRA → job burnout → service performance	direct	−0.086	0.056	−0.197	0.025
	indirect	−0.095	0.027	−0.154	−0.046
	total	−0.180	0.056	−0.291	−0.070
R–AIRA → job engagement → service performance	direct	−0.008	0.039	−0.085	0.070
	indirect	0.232	0.048	0.143	0.332
	total	0.225	0.056	0.115	0.334

Standardised coefficients are provided.
Source: Author

In summary, the study findings offer empirical support for the proposed path model, highlighting the dual role of AIRA appraisals in shaping tourism employees' service performance; demand appraisals undermine performance through heightened job burnout, while resource appraisals enhance it through increased job engagement.

5. Discussion

The potential benefits that tourism organisations can derive from AIRA can only be realised when these technologies are effectively integrated into workplace practices. Research on technology adoption consistently shows that employees' perceptions and attitudes towards technological change are critical determinants of successful implementation. Positive attitudes typically encourage efforts to acquire relevant skills and engage in functional technology use, whereas negative attitudes often lead to resistance and suboptimal technology uptake (Lichtenthaler, 2020; Trenerry et al., 2021). It is particularly important to explore these evaluative reactions in the tourism context, where the introduction of smart technologies is largely driven by organisational and market constraints that extend beyond employees' individual preferences. Moreover, some authors have suggested that employees' subjective perceptions of smart technologies exert a more substantial influence on predicting their work-related outcomes than objective characteristics of the technologies themselves (Brougham & Haar, 2018; Ding, 2021). With this perspective in mind, the present study examined how tourism employees' appraisals of AIRA in the workplace affect their service performance to shed light on the human factors that shape the effectiveness of AIRA-driven initiatives.

The findings revealed that the direction of the relationship between AIRA appraisals and service performance depended on the type of appraisal. Demand appraisals of AIRA resulted in heightened job burnout, which, in turn, negatively affected service performance. Conversely, resource appraisals of AIRA led to enhanced job engagement, which subsequently positively affected service performance. These results show some resemblance to those reported by Zhang and Jin (2023) and Quan et al. (2025), who explored the impact of intelligent technology adoption on employee attitudes and behaviours in the Chinese hospitality industry. The former, based on the two-dimensional STAARA awareness model, found that positive (vs. negative) STAARA awareness was associated with lower job insecurity and mobility. The latter, drawing on affective events theory, demonstrated that AI adoption exhibited an inverted U-shaped relationship with service performance via vigour and anxiety. Specifically, at lower levels of AI adoption, AI fostered vigour and reduced anxiety, thereby enhancing employee service performance; whereas at higher levels of AI adoption, AI depleted vigour and increased anxiety, leading to service performance deterioration.

Additionally, the present study found that tourism employees predominantly construed AIRA in the workplace as a resource rather than a demand. This suggests that, in tourism settings, employees often perceive smart technologies as tools that enhance rather than threaten their professional roles. One explanation lies in the nature of tasks performed in tourism jobs, which frequently involve relational, experiential, and emotionally intensive components. Service encounters in tourism require emotional awareness, nuanced social judgment, and authentic human interactions — capacities that, despite technological progress, remain challenging for AIRA to replicate. As proposed in the feeling economy framework (Huang, Rust, & Maksimovic, 2019; Huang & Rust, 2021), tasks that rely on empathy, contextual understanding, and interaction are the least susceptible to automation because they depend on feeling intelligence. Consequently, when successful service provision hinges on frequent and meaningful exchanges between employees and customers, AIRA are more likely to be appraised as tools of job enhancement rather than a threat.

Given the critical role of appraisals in shaping employees' attitudinal and behavioural responses, it is essential to develop a nuanced understanding of how smart technologies are perceived by organisational members. Such insights are vital for formulating strategies that facilitate the adoption of AIRA while mitigating potential risks and ensuring positive employee outcomes. The present study contributes to this understanding by demonstrating that AIRA in the workplace can be appraised both as a demand and a resource, with distinct consequences for employees' well-being and service performance. By integrating these dual appraisals, the study emphasises that technological change is not inherently detrimental or beneficial — its effects are determined by the way employees interpret and respond to it. These insights highlight the importance of adopting human-centred approaches to digital transformation in tourism, ensuring that the introduction of AIRA supports rather than undermines employees' capacity to engage in behaviours that are functional in achieving desirable customer outcomes.

6. Conclusions

This study contributes to the literature by advancing understanding of the role of AIRA appraisals in the workplace in several ways. Firstly, unlike many previous empirical investigations that addressed the effects of AIRA on work experiences and outcomes, this study demonstrates that the implementation of AIRA is not exclusively a stress-inducing work circumstance that involves coping effort. Drawing on the JD-R model, AIRA appraisals were conceptualised as dual in nature — simultaneously relating to both demands and resources of the work environment. The findings provide empirical support for this duality, revealing that AIRA appraisals can both hinder and facilitate employee performance, depending on whether they are perceived as inhibiting or enabling.

Secondly, in contrast to previous research grounded in the JD-R model, the present study refrained from making *a priori* categorisations of employees' appraisals of workplace conditions. Instead, acknowledging that such appraisals are shaped by a specific configuration of environmental factors and individual characteristics, employees' appraisals of AIRA-related work circumstances were measured directly. In this regard, the employed approach is consistent with the position of Webster, Beehr, and Love (2011), who argue that appraisals constitute the core mechanism linking workplace situations to outcomes and that work conditions may not be appraised uniformly across individuals or contexts. This view emphasises the importance of understanding how tourism employees interpret technological change, rather than assuming uniform reactions to its implementation.

Thirdly, this study provides further support for the applicability of the JD-R model (Demerouti et al., 2001) to understand the consequences of AIRA integration into tourism service delivery. Specifically, the findings revealed that demand appraisals of AIRA were associated with lower levels of service performance through heightened job burnout, whereas resource appraisals of AIRA were associated with higher levels of service performance through increased job engagement. This pattern substantiates the dual-pathway assumption of the JD-R model, demonstrating that AIRA can simultaneously activate strain and motivation processes within tourism work environments.

The findings of this study provide practical guidance for tourism organisations seeking to effectively integrate AIRA into their operations. The results suggest that employees interpret AIRA-driven changes in nuanced ways — some may primarily view these technologies as demands that threaten their job security, while others may see them chiefly as valuable resources that enhance efficiency and performance. Importantly, these appraisals are not mutually exclusive; consequently, AIRA integration can act as a double-edged sword, representing a potential source of strain that hinders performance, or a motivational force that enhances it. It is therefore essential for managers to recognise how employees appraise AIRA in the workplace and to take targeted actions that mitigate the strain pathway and strengthen the motivational one.

It is recommended that tourism organisations should cultivate an environment that fosters positive engagement with AIRA across all levels of service delivery. Clear communication about the strategic purpose of AIRA adoption is essential, and such communication should emphasise enhancements rather than replacement of human work — highlighting how AIRA can support employees in providing more seamless and personalised guest experiences. Maintaining transparency during digital transitions helps reduce uncertainty and resistance, allowing employees to feel valued and informed. Managers should also provide targeted training programs that enhance both the technical competence and the confidence required to collaborate effectively with AIRA systems in service encounters. Moreover, encouraging employee participation in the design and implementation of AIRA-enabled processes can strengthen their sense of ownership and diminish perceptions of threat. Finally, supportive leadership practices — such as recognizing employees' efforts to adapt to digital transformation and maintaining open dialogue about emerging challenges — can reinforce the perception of AIRA as a resource that assists in delivering high-quality, human-centred tourism experiences. Collectively, these actions can help transform technological change into an opportunity for growth and engagement rather than a source of strain and burnout.

7. Limitations and Future Research

There are some limitations that need to be considered when interpreting the results of this study. Firstly, the reliance on self-reported, single-source data raises the possibility of common method bias, particularly response consistency effects. Future studies could mitigate this concern by gathering data from multiple sources or employing temporal separation in data collection. Secondly, the cross-sectional design of the study limits the ability to draw causal inferences about the observed relationships. Longitudinal or experimental research would help establish the directionality of effects more robustly. Thirdly, the use of non-probability sampling and a self-selected respondents recruited via an online survey may have introduced sample bias. Moreover, as the data were collected from tourism employees in Poland, the findings cannot be easily and directly generalised to other contexts. Replication studies in different settings would therefore be valuable. Finally, this study focused on the effects of AIRA appraisals through the strain and motivation pathways. Future studies could extend this work by incorporating both antecedent and moderating variables. In particular, one could explore individual and organisational factors that shape whether employees construe AIRA as a job demand or a job resource, as well as the role of organisational interventions as potential moderators of the relationships between AIRA appraisals and performance outcomes.

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CRediT Authorship Contribution Statement

Marlena A. Bednarska: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing — original draft, writing — review & editing.

Declaration of Competing Interest

None.

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Oceny mają znaczenie: jak sztuczna inteligencja, robotyzacja i automatyzacja wpływają na poziom wykonania usługi przez pracowników sektora turystycznego

Streszczenie. Organizacje na całym świecie przechodzą głęboką transformację technologiczną wywołaną rozwojem sztucznej inteligencji, robotyzacji i automatyzacji (SIRA). Zjawisko to wpływa nie tylko na ich strukturalne i operacyjne podstawy funkcjonowania, lecz także zasadniczo przekształca charakter pracy ludzkiej. W oparciu o model wymagań i zasobów pracy autorka analizuje, w jaki sposób oceny SIRA w miejscu pracy dokonywane przez pracowników sektora turystycznego wpływają na poziom wykonania usługi, który stanowi kluczowy czynnik przewagi konkurencyjnej i źródło długoterminowego sukcesu organizacji turystycznych. Przedstawiona analiza jest oparta na danych ilościowych zebranych za pomocą ankiety internetowej od 303 pracowników sektora turystycznego w Polsce. Do weryfikacji hipotez wykorzystano hierarchiczną analizę regresji wielokrotnej oraz makro PROCESS. Wyniki wskazują na dualny charakter ocen SIRA: traktowanie ich jako wymagania obniża poziom wykonania usługi na skutek większego wypalenia zawodowego, natomiast traktowanie ich jako zasobu podnosi poziom wykonania usługi dzięki większemu zaangażowaniu w pracę. Rezultaty te podkreślają znaczenie strategii transformacji cyfrowej uwzględniających potrzeby człowieka i zapewniających, że wdrażanie SIRA wspiera pracowników zamiast zastępować ich pracę.

Słowa kluczowe: sztuczna inteligencja, robotyzacja i automatyzacja (SIRA), miejsce pracy, ocena, poziom wykonania usługi, turystyka