Proceedings of the 7th International Conference on Economics and Social Sciences (2024), ISSN 2704-6524, pp. 254-264

The 7th International Conference on Economics and Social Sciences
Exploring Global Perspectives:
The Future of Economics and Social Sciences
June 13-14, 2024
Bucharest University of Economic Studies, Romania

Artificial Intelligence and Employee Stability: The Mediating Effect of Job Engagement in Romania's Health Tourism Sector

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DOI: 10.24818/ICESS/2024/026

Abstract

This paper investigates the influence that Artificial Intelligence (AI) has on job security, which in this study includes the severity of threats (ST) and feelings of powerlessness (PO), within the Romanian health tourism sector. Additionally, we analyse how AI-driven job engagement (ENG) impacts employees' turnover intentions (TI), providing perspectives about how to maintain workforce stability. As the recent literature indicates, there is growing concern among employees in various sectors regarding to the potential that Ai have to replace human labour, mostly with a specific focus on roles requiring interpersonal skills, such as those in health tourism. Utilising the Self-Determination Theory (SDT) and also by employing a quantitative methodology, we surveyed 131 spa and hotel employees using validated and multi-item scales to measure job engagement components and job insecurity dimensions. Our results reveal significant relationships between perceived powerlessness, job engagement, and turnover intentions, showing the mediating role of job engagement. In the current study, we found that educational level moderates the relationship between perceived job, threats, and turnover intentions. This indicates an interaction between employee characteristics and perceptions of the threats that AI is bringing. With this study, we contribute both to the theoretical understanding of how AI impacts employee psychology in the market of health tourism, and also by offering insights into managing workforce transitions in the face of technological advancements.

Keywords: artificial intelligence (AI), job security, health tourism, employee turnover intentions, Romanian spa.

JEL Classification: C100; M500.

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1. Introduction

The emergence of the digital era applied to artificial intelligence utterly redefined the playing field for most industries, as it also does for health tourism, bringing many benefits for consumers and for the organisation of work (Sharma et al., 2023). However, the more extensive implementation of AI in health tourism raises a series of questions about employee perceptions of job security and how these new technologies are viewed as potential threats or opportunities. Previous research has documented that, in various industries, workers have found AI to pose a threat to their job existence; particularly, workers such as technicians and those whose jobs can be easily automated tend to fear it the most (Abdullah & Fakieh, 2020; Koo et al., 2020). In the context of health tourism, where the nature of work and the offer of empathy between the worker and the client is high, the perceived threat of AI can be identified from the relational point of view, even if interpersonal skills are still difficult for machines to replicate with ease (Huang & Rust. 2018). In their paper, Huang & Rust (2018) develop a theory of job displacement through AI, arguing that AI first replaces some job tasks and then progresses to the complete take-over of human labour. If, in the previously cited studies, the fears of employees were underlined regarding the impact of AI on job security and workforce adaptation to the new technological reality in broadly represented fields, the present study goes a step further and tries to extrapolate this research regarding the fears to a niche-focused and insufficiently researched area of activity: health tourism, at a particular moment and in a particular space context. It is equally important to explore these perceptions in the context of understanding how technological changes can be managed effectively and humanely in the health tourism sector.

2. Problem Statement

2.1 Self-Determination Theory

Self-determination theory is a psychological theory that is widely accepted by scholars, asserting that human motivation turns out to be of two types, either autonomous or either controlled; and that type and source of motivation affect types of behaviour, performance quality, and individual well-being. This theory was first introduced by Deci and Ryan in 1985, and since then SDT has been applied in the context of employee new technology adoption. Within previous research, it has been found that the adoption of new technologies was related to pleasure and acceptance only when people used it because of their intrinsic motivation (Mitchell et al., 2012). Another approach to SDT, related to new technologies, posits that perceived job insecurity influenced by the introduction of AI has a significant effect on reducing workplace commitment and increasing the intention to leave the job (Koo et al., 2020). Primarily, to the far end of our knowledge, the application of SDT to health tourism literature has not targeted employees working in this industry; for this reason, we believe that this effort to investigate the threats perceived by employees in health tourism regarding the adoption of new technologies is relevant.

2.2 Perceived Severity of Threats, Feelings of Powerlessness and Job Engagement

The previous literature has probed the meaning of job insecurity in an SDT framework in two dimensions of job insecurity: the perceived severity of a threat and powerlessness (Greenhalgh & Rosenblatt, 1984). Perceived severity is influenced by the belief in the possibility of job loss, which is amplified by adopting new technologies that replace less specialised workers. Feelings of powerlessness arise when employees believe they cannot counteract threats to the continuance of their jobs, thus enhancing the perception of risk (Greenhalgh and Rosenblatt, 1984). Job engagement is the extent to which employees show interest regarding their jobs and the organisation. It involves physical, cognitive, and emotional components (Kahn, 1990). Higher engagement is positively related to better job performance and lower turnover intentions, while job insecurity may diminish engagement (Staufenbiel & König, 2010). As explained earlier, the existing literature argues that perceived job insecurity erodes engagement, thus reducing the motivation for employees to exert effort and spend time on their tasks because of the uncertainty in their professional future. Given the above, we hypothesise the following. *H1: Perceived powerlessness directly affects the job engagement at workplace among health tourism employees; H2: Perceived severity of threats at work directly affects the job engagement at workplace among health tourism employees.*

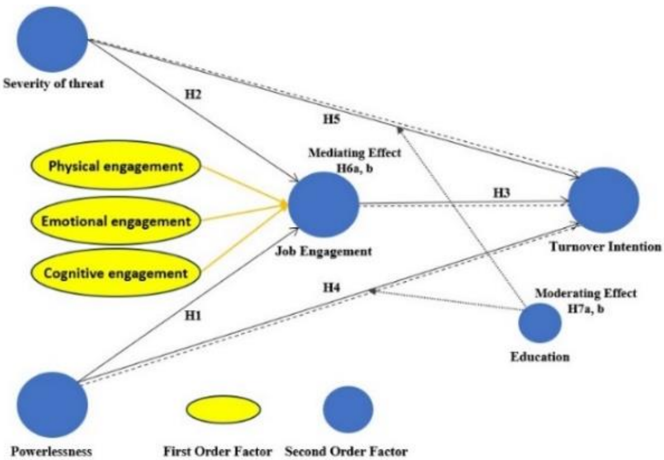
2.3 Job insecurity, Job Engagement and Turnover Intention

Job engagement (ENG) and the intention to leave the organisation (turnover intention / TI) are often analysed in the job insecurity context. Most studies denote an adverse relationship between job insecurity and commitment, suggesting that feelings of insecurity are supposed to reduce the levels of dedication and involvement in the organisation (Staufenbiel & Konig, 2010). Another relevant example of the important role engagement plays in the health tourism industry is offered by Koo et al. (2020). Their research observed how artificial intelligence affected the job security of hotel workers and found that engagement moderates the relation between job insecurity and intentions to leave the organisation. Also, Karatepe et al. (2020) found that job engagement could work as a mediator in the relationship between intentions to leave the workplace and perceived job insecurity. These results underscore the negative effects of job instability on employees and show how job engagement can decrease the risk of turnover. Therefore, we hypothesise: *H3: The job engagement directly affects the turnover intention among health tourism employees; H4: The feelings of powerlessness directly affect the turnover intention among health tourism employees; H5: The severity of the threats directly affects the turnover intention among health tourism employees; H6a: Job engagement mediates the relationship between the severity of threats and the intention to turnover in health tourism employees; H6b: Job engagement mediates the relationship between powerlessness and the intention to turnover in health tourism employees.*

2.4 Moderating Effect of Education Level

Education level is seen as a dimension that might contribute to the extent in which employees can identify with their professional group, and this will influence the motivation to remain employed within the company, despite other threats to job security posed by technology (Knippenberg, 2000). Another research regarding the implications of social identity theory for learning and development in organisations says that if education level is a moderator, that might influence the relationship between social identity and employees' engagement with professional development, is therefore needed for employees in the tourism industry, where is a constant need to adjust to the new market requirements (Koo et al., 2020). Based on the preceding discussion, we can assume that differences in education attainment among employees will have different perceptions of the threat that technological development might have on their jobs. In this regard, we postulate the following hypotheses: *H7a: Education moderates the relationship between feelings of powerlessness and turnover intention among health tourism employees; H7b: Education moderates the relationship between the severity of threats and turnover intention among health tourism employees.*

Figure 1. Proposed research model



Note: Orange lines are formative indicators and bold lines are hypotheses. Dashed lines denote mediated role (H6a, b). Dotted lines denote moderated role (H7a, b).
Source: Developed by authors.

3. Research Methods

3.1 Measurements

This study involves multi-item scales, attempting to expand the limitations that single-item scales have. We incorporate 18 items to measure six significant constructs, such as physical engagement (PE), emotional engagement (EE) and cognitive engagement (CE), all constituents of job engagement (ENG)—apart from the dimensions of job insecurity: severity of threats (ST) and powerlessness (PO), and finally, turnover intention (TI). The ST measures of evaluation were borrowed from past research, including Ashford et al. (1989) (e.g., "The change could occur in the variety of tasks I perform"). The PO measure was measured in four items based on the work of Ashford et al. (1989), with questions such as "I have sufficient authority within this organization to influence events that might impact my job". PE was measured through three items extrapolated from a study by Koo et al. (2020), such as "I will still try my hardest to perform well on my job". Similarly, EE was measured through three items also taken from Koo et al. (2020), for example, "I will still try my hardest to perform well on my job". The evaluation of EE and CE included each, three items from the same source, namely Koo et al. (2020), with items as "I will still feel positive about my job", or "At work, I will still focus a great deal of attention on my job". Behavioural intention (BI) was conceptualised based on three queries from a study by Zopiatis et al. (2014). A 7-point Likert-type scale was used as an evaluative method. The questionnaire was prepared in English and then translated into Romanian by two bilingual professionals, backtranslated into English, and carefully reviewed in case of any inconsistency.

3.2 Data Collection

Hung and Law (2011) noted that as the Internet became more widespread, more and more researchers in the field of hospitality started to use online surveys as a method to get a broader target group. This study used the Google Forms online survey questionnaire tool, while the respondents were targeted at employees of hotels and SPAs - three hotel complexes with integrated health tourism facilities (wellness and/or medical spa), arranged in three different geographical regions of Romania (seaside, mountain, capital). In total, a number of 131 questionnaires were gathered, as the data was collected from April 6 to April 17, 2024. Data as gender, age and education was measured in the questionnaire, as subjects related to demographic and social characteristics, using various scales of measurement.

3.3 Data Analysis

The collected data have been analysed in SmartPLS 4.1.02. Partial Least Squares-Structural Equation Modelling (PLS-SEM) was used to analyse the statistical influence of the independent variables used in this study on a dependent variable. In the PLS-SEM methodology, both formative and reflective indicators are examined simultaneously (Chin et al., 2010). The initial step involved in evaluating the measurement model was confirmatory factor analysis, which determined the configuration of systematically measured factors and variables within underlying constructs, thereby minimising multicollinearity or correlations of error variance among indicators (Hair et al., 2020).

4. Findings

4.1 Respondents Profile

Regarding the gender distribution of the participants, it was identified that 63.6% of the sample represented women, and 36.4% corresponded to men. Most of the participants declared having received higher education, to a percentage of 61.4%, and 38.6%, in the following order, claimed to have received up to the following levels of education: 10 grades; high school; and post-high school. In terms of age segmentation, the distribution of respondents was: 13.6% were under 25 years old, followed by 23.5% who were between 25 and 34 years old, followed by 28% between 35 and 44 years old, succeeded by 20.5% who were between 45 and 54 years old, and the seniors group, represented by 15.9% of the respondents, included participants being 55 years old or older.

4.2 Measurement Model

In this research, we used confirmatory factor analysis on the measurement model following the guidelines of Hair et al. (2020). As indicated in Table 1, 18 items were maintained for further analysis. Subsequent assessments of reliability and validity were conducted. Cronbach's alpha, a measure of internal consistency reliability, indicated that all values exceeded the recommended threshold of.700 (Taber, 2017), (CR) composite reliability tests, which also assess internal consistency between measurement items, showed all values were above the.600 guideline (Ringle et al., 2018), with figures ranging from .917 to .983. For evaluating the convergent and discriminant validity, the values average variance extracted (AVE) were calculated, all surpassing the minimum recommended value of .50, with a range of.788 to.952. Moreover, all squared AVE values were higher than the correlations between any pair of constructs (Fornell & Larcker, 1981). Therefore, the reliability and validity are thoroughly established.

Table 1. The results of measurement model (n=131)

Variable	CE	EE	PE	TI	PO	ST	Factor loading	Cronbach's α	CR	AVE (√AVE)
CE								.971	0.981	.945
CE1	1						.965			(.972)
CE2							.985			
CE3							.967			
EE								.975	0.983	0.952
EE1	.790	1					.974			(.975)
EE2							.973			
EE3							.979			
PE								.963	.976	.932
PE1	.801	.766	1				.967			(.965)
PE2							.979			
PE3							.950			

Variable	CE	EE	PE	TI	PO	ST	Factor loading	Cronbach's α	CR	AVE (√AVE)
TI								.925	.952	.869
TI1	.184	.172	.072	1			.910			(.932)
TI2							.938			
TI3							.948			
PO								.865	.917	.788
PO1							.814			(.888)
PO2	.485	.480	.566	.113	1		.926			
PO3							.918			
ST								.878	.925	.804
ST1							.869			(.897)
ST2							.933			
ST3	.212	.208	.265	.418	.342	1	.888			

Source: Developed by the authors based on calculations from SmartPLS.

ENG is quantified as a formative variable comprising three sub-constructs, making it a Second Order Factor (SOF) in the study, based on three First Order Factors (FOF): CE, EE, and PE. This formative approach identifies several attributes, each with multiple dimensions. To establish the validity of the SOF, outer weights, *t*-statistics, *p*-values, outer loadings, and the VIF were checked (see Table 2). The outer loadings were strong (Hair et al., 2020) and more significant than the rule of thumb of 0.50 for all SOFs (Sarstedt et al., 2019). Multicollinearity has also been checked using VIF values, indicating them below the threshold of 5 (Hair et al., 2020). According to the previous status, the SOF is agreed to be valid.

Table 2. Second Order Factor (SOF) Validity

SOF	FOF	Outer Weight	T Statistics	P Values	Outer Loadings	VIF
ENG	CE	0.189	0.649	0.258	0.872	3.168
	EE	0.206	0.859	0.195	0.853	2.807
	PE	0.676	2.331	0.010	0.975	2.885

Source: Developed by the authors based on calculations from SmartPLS.

4.3 Structural Model

The structural model displays the paths between constructs in the proposed study model. The R2 values are 29.4% for job engagement, and 45.4% for behavioural intention. Given the absence of multivariate normality in the data, path estimates and *t*-statistics for these relationships were analysed using the bootstrapping method (Hair et al., 2020). We used the PLS bootstrap method to assess the sampling distribution's shape non-parametrically by involving 5000 resampling. H1 assesses whether PO is positively related to ENG. The results showed PO with a significant impact on ENG (β=0.508, t=7.263, p=0.000). Consequently, H1 is accepted.

H2 exposes if ST has a significant impact on ENG. Our results showed that ST does not have a significant impact on ENG (β=0.090, t=1.020, p>0.05), this meaning that H2 is rejected. H3 assesses whether ENG has a significant impact on TI. The results indicated that ENG has a significant negative impact on TI (β = -0.232, t = 3.406, p = 0.000), so H3 is accepted. In the next relation, PO has a significant impact on TI (β = 0.148, t = 2.010, p = 0.022), so H4 is also accepted. The results showed that ST has a significant impact on TI (β=0.142, t=1.859, p= 0.032), therefore, H5 is accepted.

4.4 Mediation Analysis

H6a assesses whether ENG mediates the relationship between ST and TI. The results show that the total effect (H5) was found positive and insignificant (β=0.121, t=1.557, p=0.060). When we introduced the mediator into the model, the direct effect remained significant (β = 0.142, t = 1.859, p = 0.032), and the indirect effect with the inclusion of the mediator in the analysis was also found to be insignificant (β = -0.020, t = 0.963, p =0.168). This shows that the effect of ST on TI does not pass through ENG, and therefore, H6a is rejected.

H6b assesses whether ENG mediates the relationship between PO and TI. Because PO has a significant impact on TI (β=0.148, t=2.010, p=0.022) and the indirect effect with inclusion of the mediator in the analysis was found to be negative and significant (β=-0.118, t=2.942, p=0.003). The results reveal a partial mediation. This shows that the effect of PO on TI partially passes through ENG. Therefore, H6b is accepted.

4.5 Moderation Analysis

For the moderation analysis presented in this study, we proposed H7a: Education does not moderate the relationship between PO and TI (β=-0.001, t=0.008, p>0.5), so H7a is rejected. H7b: Education positively moderates the positive relationship between ST and TI, so that increased education strengthens the relationship between ST and TI. The obtained results assessed the moderating role of education on the relationship between ST and TI. Without the inclusion of the moderating effect (STxEdu), the R2 for TI was .224. This shows that the 22.4% change in TI is accounted for by ST. With the inclusion of the interaction term, the R2 increased to 45.4%. This shows an increase of 45.4% in variance explained in the dependent variable (TI). Furthermore, the significance of the moderating effect was analysed, the results revealed a positive and significant moderating impact of Edu on the relationship between ST and TI (β=0.427, t=2.567, p=0.010), supporting H7b. F-Square effect size was .071, and according to Cohen (1988) proposition, 0.02, 0.15 and 0.35 constitute small, medium, and large effect sizes of moderation respectively. There is a small to medium significant moderating effect, and this shows that moderating effect does contribute in explaining the endogenous construct (TI).

5. Conclusions

This study investigated the effects of AI on job security in Romania's health tourism sector, focussing on the severity of threats and feelings of powerlessness and their influence on job engagement and turnover intentions. The results showed that, contrary to our expectations, the perceived severity of AI-related threats did not significantly influence job engagement. This finding contrasts with the premise suggested by Greenhalgh and Rosenblatt (1984) that perceived job threats reduce employee engagement. Perhaps employees in the health tourism sector are aware that, with AI, roles that are unique to their professions and call for interpersonal skills, such as empathy and communication, are less threatened, which could reduce the perception of threat to their jobs (Abdullah & Fakieh, 2020). However, powerlessness significantly lowered job engagement, which is consistent with the earlier assertion by Greenhalgh and Rosenblatt (1984) that powerless employees withdraw from their roles. Job engagement was, in turn, a significant negative predictor of turnover intentions, thereby supporting the assertion by Karatepe et al. (2020). In addition, feelings of powerlessness and the severity of the perceived threats directly impacted turnover intentions, thus reinforcing the notion that employees who feel unable to influence job security-related events are more likely to consider leaving (Koo et al., 2020). Besides, the mediation analysis established that job engagement proved to be a partial mediator in the feelings of powerlessness and turnover intentions since the feelings of powerlessness directly affect turnover intentions and an indirect impact through job engagement. The level of education moderated the relationship between perceived severity and turnover intentions, pointing toward the fact that employees with high educational levels are sensitive to the perceived job threats that AI may pose. However, no significant moderating effect on feelings of powerlessness and turnover intentions was discovered. Job engagement strategies should be at the top of the organisational agenda, and educational and training opportunities can be given to minimise anxieties arising from the employment of AI, providing a hint into how workforce transitions could be managed amid advancements in technology.

Acknowledgment

This paper was co-financed by the Bucharest University of Economic Studies during the PhD program.

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