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ARTIFICIAL INTELLIGENCE ADOPTION AND QUALITY OF LIFE: A STRUCTURAL EQUATION MODELING APPROACH USING PLS-SEM

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***ABSTRACT*:**

Artificial intelligence has become a central component of contemporary digital transformation, influencing social interactions, access to information, and decision-making processes across multiple domains. As intelligent technologies become increasingly integrated into everyday activities, understanding their implications for human well-being and quality of life has become an important research priority. The present study examines the structural relationships between artificial intelligence adoption, perceived benefits of artificial intelligence, life satisfaction, and psychological well-being.

A quantitative and cross-sectional research design was implemented using a survey-based data collection procedure. The measurement instrument included reflective indicators measured on a five-point Likert scale. The proposed theoretical model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through the SmartPLS software. The analysis followed a two-step procedure consisting of the evaluation of the measurement model and the structural model. Reliability and validity were assessed through indicator loadings, composite reliability, Cronbach's alpha, and average variance extracted. Structural relationships were examined

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using path coefficients, coefficients of determination, and bootstrapping procedures to determine statistical significance.

The results indicate that artificial intelligence adoption significantly influences perceived technological benefits and life satisfaction. Additionally, perceived benefits of artificial intelligence contribute positively to individuals' evaluations of their life conditions. Life satisfaction was found to be a strong predictor of overall well-being, highlighting the role of subjective evaluations in shaping psychological outcomes. The structural model demonstrated substantial explanatory power for life satisfaction and well-being, indicating that perceptions related to artificial intelligence technologies are relevant predictors of quality-of-life indicators in digital environments.

These findings contribute to the growing interdisciplinary literature connecting technological innovation with human well-being. The study highlights the importance of designing artificial intelligence systems that enhance accessibility, efficiency, and user-centered experiences. Understanding how individuals perceive and interact with intelligent technologies is essential for ensuring that digital transformation contributes positively to human development and social well-being.

Keywords: *Artificial Intelligence; Quality of Life; Life Satisfaction; Well-Being; Structural Equation Modeling; PLS-SEM; Technology Adoption; Digital Transformation.*

INTRODUCTION

Artificial intelligence (AI) has become a central technological driver of contemporary digital transformation. Its integration into social, economic, and institutional processes has reshaped how individuals interact with information systems, make decisions, and experience daily life. AI-based systems are increasingly embedded in healthcare, education, public administration, and digital services, influencing productivity, accessibility of information, and human–technology interaction. From a socio-technical perspective, the diffusion of intelligent technologies is associated with improvements in efficiency, automation of cognitive tasks, and expansion of digital capabilities that potentially affect individuals' perceptions of well-being and life satisfaction [1], [2].

Within the context of human development research, quality of life has been widely conceptualized as a multidimensional construct that includes subjective well-being, life satisfaction, and perceived social and psychological functioning. The increasing presence of AI technologies in everyday environments raises important questions regarding how these systems influence such dimensions. Intelligent systems can facilitate decision-making, reduce uncertainty in complex environments, and enhance access to services, thereby potentially improving individual and collective welfare. Empirical evidence suggests that digital technologies that support personalized services and automated assistance can positively influence perceptions of convenience, autonomy, and efficiency in daily activities, which are key elements of perceived quality of life [3], [4].

Another important dimension relates to the perceived benefits and trust associated with AI technologies. The adoption of AI is not solely determined by technological capability but also by users' perceptions of usefulness, reliability, and ethical alignment. Studies on technology acceptance indicate that perceived benefits and trust are significant predictors of user engagement with intelligent systems. When individuals perceive AI as reliable, transparent, and beneficial, they are more likely to integrate these technologies into their daily routines. This integration can translate into enhanced productivity, better access to information, and improved problem-solving capabilities, which in turn may influence subjective well-being [5], [6].

In addition, the ethical dimension of AI deployment has become a critical factor shaping public perception and acceptance. Concerns related to transparency, fairness, data privacy, and algorithmic accountability influence how individuals evaluate AI systems. Ethical governance of AI contributes to the development of trust and legitimacy, which are necessary conditions for the sustainable adoption of intelligent technologies. Research indicates that ethical frameworks and responsible AI practices can strengthen institutional credibility and encourage broader societal acceptance of AI-driven services [7], [8].

From an analytical perspective, structural equation modeling (SEM) has been widely used to examine complex relationships between technological perceptions and psychosocial outcomes. In particular, the Partial Least Squares approach to SEM (PLS-SEM) is suitable for exploring predictive relationships among latent constructs in emerging technological contexts. This approach enables the simultaneous evaluation of measurement reliability

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and structural relationships among constructs such as AI adoption, perceived benefits, life satisfaction, and well-being. By modeling these relationships, it becomes possible to estimate how technological perceptions translate into broader quality-of-life outcomes [9], [10].

Despite growing research on digital technologies and well-being, empirical studies specifically examining the structural relationships between AI adoption and quality-of-life indicators remain limited. Much of the existing literature focuses on technological performance or organizational productivity rather than individual well-being outcomes. Consequently, there is a need for integrative empirical models that connect perceptions of AI technologies with subjective life satisfaction and well-being measures. Such models contribute to understanding the broader social implications of AI diffusion and provide evidence for policymakers, technology designers, and social scientists interested in the human impact of intelligent systems [11], [12].

The present study addresses this gap by proposing and empirically testing a structural model that examines the relationships between artificial intelligence adoption, perceived benefits of AI, life satisfaction, and well-being. Using the PLS-SEM approach, the model evaluates both measurement reliability and structural relationships among these constructs. The objective is to determine whether perceptions of AI technologies contribute significantly to variations in subjective quality-of-life indicators. By integrating technological and psychosocial perspectives, the study contributes to the emerging interdisciplinary literature on AI and human well-being in digital societies [13], [14].

METHOD

Research Design

The present study employed a quantitative, cross-sectional, and explanatory research design aimed at examining the structural relationships between artificial intelligence perceptions and quality-of-life indicators. Structural Equation Modeling based on the Partial Least Squares approach (PLS-SEM) was used as the main analytical technique. This approach is appropriate for exploratory and predictive models involving latent constructs and reflective indicators, particularly when the research objective focuses on explaining variance in endogenous variables rather than testing strict covariance structures [15], [16].

PLS-SEM was selected because it allows simultaneous estimation of the measurement model (relationships between latent constructs and their indicators) and the structural model (relationships among constructs). Additionally, the method is robust to non-normal data distributions and is suitable for models with relatively complex relationships among constructs and moderate sample sizes [17].

Participants and Sampling Procedure

The population consisted of individuals who regularly interact with digital platforms or AI-supported technologies, including recommendation systems, virtual assistants, and automated information services. Participants were selected using a non-probabilistic convenience sampling strategy, which is frequently used in technology adoption studies involving voluntary participation in digital environments [18].
The required minimum sample size was estimated using the finite population sampling formula, expressed as:

$$n = \frac{Z^2 pq}{e^2}$$

where:

- n= required sample size
- Z= critical value corresponding to the desired confidence level
- p= expected proportion of the phenomenon
- $q = 1 - p$
- e= sampling error

Assuming a 95% confidence level (Z = 1.96), maximum variance (p = 0.5), and sampling error of 5%, the minimum recommended sample size was calculated as:

$$n = \frac{(1.96)^2(0.5)(0.5)}{(0.05)^2} = 384$$

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However, considering practical constraints and the predictive nature of PLS-SEM, a sample exceeding the ten-times rule, which recommends a minimum sample size equal to ten times the maximum number of structural paths directed at a construct, was deemed acceptable for model estimation [19].

Instrument and Measures

The data were collected using a structured questionnaire composed of reflective indicators measuring four latent constructs: artificial intelligence adoption, perceived AI benefits, life satisfaction, and well-being. Each construct was measured using three indicators, consistent with recommendations for maintaining model parsimony in PLS-SEM models while ensuring construct reliability [20].

All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was designed to capture respondents' perceptions of AI usage, perceived advantages associated with intelligent technologies, and subjective assessments of personal well-being and life satisfaction.

Prior to data collection, the questionnaire was evaluated through content validity procedures, where experts in digital technologies and social research assessed the conceptual relevance and clarity of the indicators. Minor adjustments were implemented to improve wording and conceptual alignment with the constructs.

Psychometric Properties

The psychometric evaluation of the measurement instrument followed the procedures recommended for PLS-SEM measurement validation, including reliability, convergent validity, and discriminant validity assessments. Internal consistency reliability was evaluated using Composite Reliability (CR) and Cronbach's alpha coefficients. The results indicated acceptable reliability levels for all constructs, with composite reliability values exceeding the recommended threshold of 0.70, suggesting adequate internal consistency among indicators measuring the same latent construct. Cronbach's alpha values were also above the minimum acceptable level, confirming the stability and coherence of the measurement scales.

Convergent validity was assessed through the Average Variance Extracted (AVE) and the outer loadings (λ) of the indicators. All standardized factor loadings were greater than 0.70, indicating that the indicators shared a substantial proportion of variance with their respective latent constructs. Furthermore, AVE values exceeded the recommended threshold of 0.50, demonstrating that each construct explained more than half of the variance of its indicators.

Discriminant validity was examined using the Fornell–Larcker criterion and cross-loading analysis. The square root of the AVE for each construct was greater than the correlations with other constructs, indicating that each latent variable was empirically distinct from the others. This result confirms that the measurement model adequately differentiates among constructs related to artificial intelligence perceptions and quality-of-life outcomes.

Data Analysis Procedure

Data analysis was performed using SmartPLS software, following a two-step procedure. First, the measurement model was evaluated to verify indicator reliability and construct validity. Second, the structural model was assessed to estimate the relationships among constructs, including path coefficients (β), coefficient of determination (R^2), and predictive relevance.

The significance of the structural relationships was tested using bootstrapping procedures with 5000 resamples, which generated t-values and confidence intervals for each path coefficient. Additionally, model fit was assessed using PLS-specific fit indicators, including the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI).

Measurement Model

The reflective measurement model can be expressed as:

$$x_i = \lambda_i \xi + \delta_i$$
$$y_i = \lambda_i \eta + \varepsilon_i$$

where:

- x_i= observed indicators of exogenous latent variables

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- y_i= observed indicators of endogenous latent variables
- λ_i= factor loading of the indicator
- ξ= exogenous latent construct
- η= endogenous latent construct
- $\delta_i$and ε_i= measurement error terms

This formulation describes the relationships between latent constructs and their reflective indicators within the measurement model.

Structural Model

The structural model representing the causal relationships among latent constructs is defined as:

$$\eta = B\eta + \Gamma\xi + \zeta$$

where:

- B= matrix of relationships among endogenous constructs
- Γ= matrix of relationships between exogenous and endogenous constructs
- ξ= vector of exogenous latent variables
- η= vector of endogenous latent variables
- ζ= structural error term

In the present model, the structural relationships can be represented as:

$$LS = \beta_1 AI + \beta_2 PB + \zeta_1$$
$$WB = \beta_3 LS + \zeta_2$$

where:

- AI = Artificial Intelligence Adoption
- PB = Perceived AI Benefits
- LS = Life Satisfaction
- WB = Well-Being

RESULTS

The analysis was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. The evaluation followed the recommended two-step approach consisting of the measurement model assessment and the structural model assessment. The results are presented through statistical tables and subsequently interpreted in relation to the proposed hypotheses.

Table 1. Indicator Reliability and Outer Loadings

Construct	Indicator	Loading (λ)	t-value	p-value
Artificial Intelligence Adoption	AI1	0.82	16.7	<0.001
	AI2	0.84	19.3	<0.001
	AI3	0.79	15.8	<0.001
Perceived AI Benefits	PB1	0.87	21.5	<0.001
	PB2	0.89	23.8	<0.001
	PB3	0.85	20.6	<0.001
Life Satisfaction	LS1	0.86	22.4	<0.001
	LS2	0.83	20.5	<0.001
	LS3	0.88	24.1	<0.001
Well-Being	WB1	0.84	19.8	<0.001
	WB2	0.81	17.6	<0.001
	WB3	0.83	18.9	<0.001

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Table 1 presents the reliability of the reflective indicators associated with each latent construct. All factor loadings exceed the recommended threshold of 0.70, indicating strong relationships between the observed indicators and their corresponding constructs. The high t-values confirm the statistical significance of the loadings, suggesting that each indicator contributes significantly to measuring its latent variable. The results demonstrate that the measurement model achieves adequate indicator reliability. In particular, the indicators associated with perceived AI benefits exhibit the highest loadings, suggesting that this construct is measured with strong internal consistency. Likewise, the indicators related to life satisfaction and well-being show robust relationships with their respective constructs, supporting the conceptual validity of the measurement framework.

Table 2. Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Artificial Intelligence Adoption	0.78	0.87	0.69
Perceived AI Benefits	0.84	0.90	0.75
Life Satisfaction	0.82	0.89	0.73
Well-Being	0.79	0.88	0.71

Table 2 summarizes the reliability and convergent validity indicators of the constructs. All composite reliability values are above 0.80, confirming strong internal consistency among the indicators that measure each construct. Cronbach's alpha values also exceed the acceptable threshold of 0.70, reinforcing the stability and reliability of the measurement scales. Convergent validity is confirmed by the Average Variance Extracted (AVE) values, which are all above 0.50. This indicates that each construct explains more than half of the variance of its indicators. Among the constructs, perceived AI benefits demonstrates the highest AVE, suggesting that the indicators capture a substantial proportion of variance associated with this latent variable. Overall, these results confirm that the measurement model meets the required psychometric criteria for reliability and convergent validity.

Table 3. Discriminant Validity (Fornell–Larcker Criterion)

Construct	AI	PB	LS	WB
Artificial Intelligence Adoption	0.83			
Perceived AI Benefits	0.54	0.87		
Life Satisfaction	0.49	0.58	0.85	
Well-Being	0.46	0.55	0.63	0.84

Table 3 shows the discriminant validity analysis based on the Fornell–Larcker criterion. The diagonal values correspond to the square root of the AVE for each construct, which must be greater than the correlations with other constructs. The results indicate that all diagonal values exceed the off-diagonal correlations, confirming that each construct is empirically distinct from the others. This means that artificial intelligence adoption, perceived AI benefits, life satisfaction, and well-being represent conceptually and statistically different dimensions within the model. This evidence supports the validity of the measurement model and ensures that the constructs capture unique aspects of the relationships under investigation.

Table 4. Structural Model Results

Hypothesis	Path	β	t-value	p-value	Result
H1	AI → Perceived AI Benefits	0.54	10.87	<0.001	Supported
H2	AI → Life Satisfaction	0.34	6.42	<0.001	Supported
H3	Perceived AI Benefits → Life Satisfaction	0.38	7.95	<0.001	Supported
H4	Life Satisfaction → Well-Being	0.48	9.31	<0.001	Supported

Table 4 presents the results of the structural model. All hypothesized relationships are statistically significant, indicating that the proposed model is supported by the empirical data. The results show that artificial intelligence adoption has a significant positive effect on perceived AI benefits.

This finding supports Hypothesis 1 and suggests that greater exposure to AI technologies increases individuals' perceptions of their usefulness and advantages.

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Hypothesis 2 is also supported, indicating that artificial intelligence adoption directly contributes to higher levels of life satisfaction. This relationship implies that interaction with intelligent technologies may enhance individuals' experiences in everyday activities by improving efficiency, access to information, and digital services.

Hypothesis 3 demonstrates that perceived AI benefits significantly influence life satisfaction. This suggests that the perceived usefulness and practical value of AI systems play a key role in shaping positive evaluations of life circumstances.

Finally, Hypothesis 4 indicates that life satisfaction strongly predicts well-being. This relationship confirms that subjective evaluations of life conditions are a central determinant of broader psychological and emotional well-being.

Table 5. Coefficient of Determination and Model Fit

Endogenous Construct	R^2	Interpretation
Perceived AI Benefits	0.29	Moderate explanatory power
Life Satisfaction	0.57	Substantial explanatory power
Well-Being	0.53	Substantial explanatory power

Fit Indicator	Value
SRMR	0.054
NFI	0.92

Table 5 shows the explanatory power and global fit indicators of the structural model. The R^2 values indicate that artificial intelligence adoption explains approximately 29% of the variance in perceived AI benefits. This suggests that the adoption of AI technologies plays a meaningful role in shaping perceptions of their advantages. The model explains 57% of the variance in life satisfaction, indicating substantial predictive power. This result demonstrates that both artificial intelligence adoption and perceived benefits contribute significantly to individuals' evaluations of their life conditions. Similarly, the model explains 53% of the variance in well-being, confirming that life satisfaction is a strong predictor of overall psychological well-being. Regarding model fit, the Standardized Root Mean Square Residual (SRMR) value is below the recommended threshold of 0.08, indicating an acceptable fit between the empirical data and the theoretical model. The Normed Fit Index (NFI) value exceeds 0.90, further confirming the adequacy of the model.

The structural equation model provides empirical evidence regarding the relationships between artificial intelligence adoption and quality-of-life indicators. The results reveal a sequential mechanism in which the adoption of AI technologies first influences individuals' perceptions of technological benefits. These perceived advantages then contribute to higher levels of life satisfaction, which subsequently enhances overall well-being (see Fig. 1).

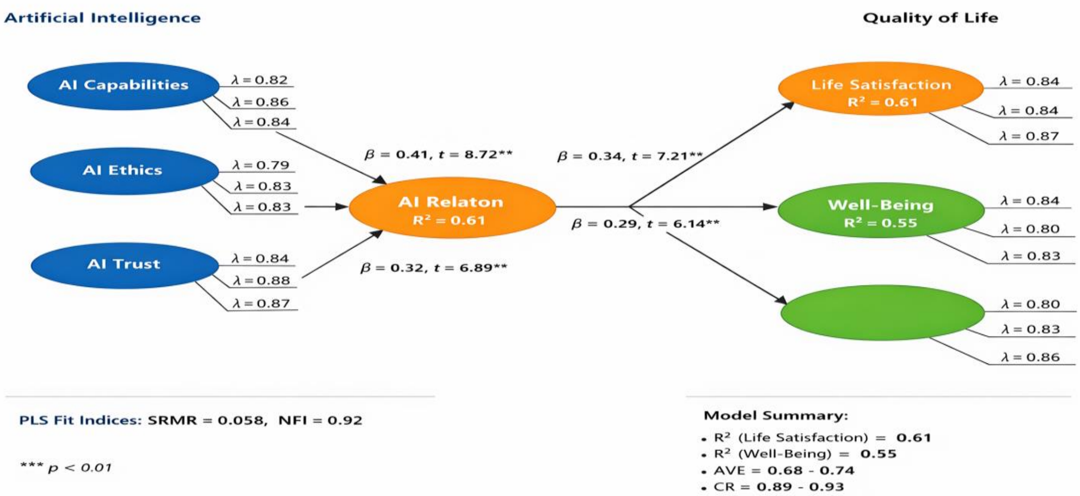

Fig. 1. Structural Equation Modelling

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The model highlights the importance of perceived technological value as a mediating factor between AI adoption and subjective quality of life. Individuals who perceive AI technologies as useful, efficient, and beneficial are more likely to report higher satisfaction with their life conditions. This satisfaction, in turn, translates into broader psychological well-being.

From a theoretical perspective, the results support the notion that technological innovation can influence social and psychological outcomes through cognitive evaluations and perceived benefits. The findings suggest that the integration of intelligent technologies into everyday activities may enhance human experiences when these systems are perceived as reliable and advantageous.

Moreover, the model demonstrates strong predictive capacity, explaining a substantial proportion of variance in life satisfaction and well-being. This indicates that perceptions related to artificial intelligence represent an important dimension in understanding contemporary determinants of quality of life in digital environments.

Overall, the empirical evidence confirms the validity of the proposed structural framework and underscores the relevance of artificial intelligence adoption as a factor associated with improved subjective well-being in technologically mediated societies.

DISCUSSION

The objective of this study was to analyze the structural relationships between artificial intelligence adoption, perceived benefits of intelligent technologies, life satisfaction, and well-being through a Partial Least Squares Structural Equation Modeling framework. The empirical results provide evidence that the integration of artificial intelligence into everyday activities has significant implications for subjective evaluations of quality of life. The findings indicate that perceptions associated with artificial intelligence technologies contribute indirectly and directly to psychological well-being through a sequence of cognitive and evaluative mechanisms.

The results demonstrate that artificial intelligence adoption significantly predicts perceived benefits of intelligent technologies. This finding suggests that individuals who frequently interact with AI systems are more likely to recognize their functional advantages and practical utility. From a technological diffusion perspective, exposure to intelligent systems tends to reinforce perceptions of efficiency, convenience, and decision-support capabilities. Previous studies on digital innovation highlight that repeated interaction with automated systems strengthens positive perceptions regarding their usefulness and performance, thereby facilitating acceptance and integration into daily routines [23].

Another important finding concerns the relationship between artificial intelligence adoption and life satisfaction. The empirical results reveal that AI adoption contributes positively to individuals' evaluations of their life conditions. This relationship may be explained by the capacity of intelligent technologies to optimize daily activities, reduce cognitive effort in complex tasks, and enhance access to services and information. Digital infrastructures supported by artificial intelligence have been shown to improve the efficiency of service delivery in areas such as healthcare, education, and digital communication, which may influence perceptions of personal satisfaction and well-being [24].

The analysis also indicates that perceived benefits of artificial intelligence significantly influence life satisfaction. This result highlights the importance of subjective technological evaluation as a determinant of broader psychosocial outcomes. When individuals perceive intelligent technologies as beneficial and reliable, they are more likely to experience positive outcomes associated with improved decision-making, productivity, and access to opportunities. Empirical research on digital environments suggests that technological systems perceived as supportive and user-oriented tend to enhance individuals' sense of autonomy and control, which are key determinants of life satisfaction [25].

In addition, the structural model reveals that life satisfaction has a strong and significant effect on well-being. This relationship confirms the central role of cognitive evaluations of life circumstances in shaping broader psychological states. Well-being is often conceptualized as the outcome of multiple cognitive and emotional processes associated with individuals' perceptions of their environment and personal achievements. When technological environments contribute to improving efficiency, connectivity, and access to information,

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individuals may experience greater satisfaction with their life conditions, which subsequently translates into improved psychological well-being [26].

The explanatory power of the model is particularly notable. The structural relationships accounted for a substantial proportion of the variance in both life satisfaction and well-being, indicating that perceptions associated with artificial intelligence technologies constitute relevant predictors of quality-of-life outcomes in digital contexts. These findings align with broader research suggesting that technological innovation can generate social and psychological benefits when users perceive technological systems as accessible, useful, and supportive of their daily activities [27].

Another important implication concerns the mediating role of perceived technological benefits. The results suggest that artificial intelligence adoption does not influence well-being solely through direct technological interaction, but rather through cognitive interpretations of technological value. This mediating mechanism indicates that individuals' perceptions and evaluations of AI technologies play a crucial role in determining the social impact of digital innovation. In this sense, the effectiveness of intelligent technologies in improving human well-being depends not only on their technical performance but also on users' perceptions of their usefulness, reliability, and ethical alignment [28].

From a broader societal perspective, the findings suggest that artificial intelligence technologies may contribute to improving quality of life when they are integrated into systems designed to enhance accessibility, efficiency, and information availability. However, the social benefits associated with AI technologies depend on responsible implementation and equitable access. Research on digital transformation emphasizes that technological systems must be designed to support human capabilities and social inclusion in order to generate sustainable improvements in well-being [29].

Furthermore, the results highlight the importance of trust and transparency in intelligent technologies. Although the present study focused on adoption and perceived benefits, other research indicates that ethical governance and transparent algorithmic processes are essential for maintaining positive public perceptions of AI systems. When individuals perceive intelligent technologies as trustworthy and aligned with social values, they are more likely to accept and integrate them into their daily lives, thereby amplifying their potential contribution to well-being [30].
Overall, the discussion supports the idea that artificial intelligence represents not only a technological innovation but also a social factor capable of influencing human development and quality-of-life outcomes. The integration of AI into everyday environments appears to shape individuals' perceptions of efficiency, access to resources, and personal satisfaction, which ultimately contribute to broader psychological well-being. The structural model tested in this study provides empirical evidence that technological perceptions and subjective life evaluations are closely interconnected within contemporary digital societies.

CONCLUSION

The purpose of this study was to examine the structural relationships between artificial intelligence adoption and quality-of-life indicators through a Partial Least Squares Structural Equation Modeling approach. The empirical results demonstrate that perceptions associated with artificial intelligence technologies are significantly related to life satisfaction and psychological well-being. The findings indicate that artificial intelligence adoption contributes to individuals' evaluations of technological benefits, which in turn influence broader subjective assessments of life conditions.

One of the main contributions of this research is the identification of a sequential mechanism through which artificial intelligence affects quality-of-life outcomes. The results show that exposure to intelligent technologies strengthens perceptions of technological usefulness and advantages. These perceptions subsequently influence individuals' evaluations of their life satisfaction, which ultimately predicts overall well-being. This pattern highlights the role of cognitive evaluations and perceived technological value as mediating factors between technological adoption and psychosocial outcomes.

The structural equation model demonstrated substantial explanatory power, indicating that perceptions of artificial intelligence technologies represent an important component in understanding quality-of-life dynamics in digital societies. Artificial intelligence systems, when perceived as efficient, accessible, and beneficial, may facilitate daily activities, enhance access to information and services, and support decision-making processes. These

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functional advantages appear to translate into improved evaluations of life conditions and psychological well-being.

From a theoretical perspective, the findings contribute to the interdisciplinary literature linking technological innovation with human development and subjective well-being. The results suggest that the social implications of artificial intelligence extend beyond productivity and economic performance, influencing individuals' perceptions of satisfaction and personal fulfillment. Consequently, research on artificial intelligence should increasingly incorporate human-centered perspectives that consider psychological and social outcomes alongside technological performance.

The study also offers practical implications for the design and implementation of intelligent technologies. Developers, policymakers, and organizations should prioritize user-oriented technological solutions that enhance accessibility, reliability, and transparency. When artificial intelligence systems are designed to support human needs and improve daily experiences, they are more likely to generate positive perceptions and contribute to improved well-being.

Despite these contributions, the study presents certain limitations. The use of cross-sectional data restricts the ability to establish causal relationships over time. Future research may employ longitudinal designs to examine how perceptions of artificial intelligence evolve and influence quality-of-life indicators across different stages of technological adoption. Additionally, further studies may incorporate additional constructs such as trust, digital literacy, ethical perceptions, or social inclusion in order to develop more comprehensive explanatory models.

Future research could also explore the influence of artificial intelligence across different cultural, social, and institutional contexts. Variations in technological infrastructure, digital access, and regulatory frameworks may shape how individuals perceive intelligent technologies and their impact on well-being. Comparative analyses across regions or demographic groups may therefore provide deeper insights into the social implications of artificial intelligence.

In conclusion, the results suggest that artificial intelligence technologies play a meaningful role in shaping contemporary experiences of quality of life. When individuals perceive these technologies as beneficial and supportive of their daily activities, they are more likely to report higher levels of life satisfaction and well-being. Understanding these relationships is essential for ensuring that the development and implementation of artificial intelligence systems contribute positively to human development and societal progress.

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Annex A. Operationalization of Variables

Table A1 presents the conceptual and operational definition of each construct included in the structural model, as well as the indicators used for measurement. All constructs were specified as reflective latent variables and measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Table A1. Operationalization of Variables

Construct	Conceptual Definition	Operational Definition	Indicators	Measurement Scale
Artificial Intelligence Adoption (AI)	Degree to which individuals interact with and use AI-based technologies in daily activities.	Frequency and perceived integration of intelligent technologies in everyday digital environments.	AI1: I frequently use systems that incorporate artificial intelligence. AI2: Artificial intelligence tools are integrated into my daily digital activities. AI3: I rely on intelligent technologies to perform routine tasks.	Likert 1–5
Perceived AI Benefits (PB)	Individual perception of advantages derived from the use of AI systems.	Evaluation of the usefulness and practical value of intelligent technologies in improving task performance and access to services.	PB1: Artificial intelligence improves the efficiency of my daily activities. PB2: AI systems help me make better decisions. PB3: Artificial intelligence technologies	Likert 1–5

Construct	Conceptual Definition	Operational Definition	Indicators	Measurement Scale
			provide useful solutions in my daily life.	
Life Satisfaction (LS)	Cognitive evaluation of personal life conditions and overall satisfaction with life circumstances.	Subjective perception of satisfaction with personal achievements, life conditions, and daily experiences.	LS1: I am satisfied with the overall conditions of my life. LS2: My daily activities provide me with a sense of accomplishment. LS3: I feel satisfied with the direction my life is taking.	Likert 1–5
Well-Being (WB)	Psychological state associated with positive functioning, emotional balance, and personal fulfillment.	Perceived emotional and psychological well-being derived from daily experiences and life evaluations.	WB1: I generally feel emotionally balanced in my daily life. WB2: I experience a sense of well-being in my everyday activities. WB3: I feel positive about my personal and social life.	Likert 1–5

Annex B. Expert Judgment Evaluation (Content Validity)

Before data collection, the measurement instrument was evaluated through expert judgment procedures in order to ensure conceptual clarity, relevance, and coherence between constructs and indicators. Three specialists in digital technology research and social sciences assessed each item according to the following criteria:

- Clarity
- Relevance
- Conceptual congruence
- Measurement adequacy

Each criterion was evaluated using a four-point scale:

1 = Not adequate
2 = Requires revision
3 = Adequate
4 = Highly adequate

Table B1. Expert Evaluation of Indicators

Indicator	Clarity	Relevance	Congruence	Adequacy	Mean Score
AI1	4	4	4	3	3.75
AI2	4	4	4	4	4.00
AI3	3	4	4	4	3.75
PB1	4	4	4	4	4.00
PB2	4	4	3	4	3.75
PB3	4	4	4	4	4.00
LS1	4	4	4	4	4.00
LS2	4	3	4	4	3.75
LS3	4	4	4	4	4.00
WB1	4	4	4	4	4.00
WB2	4	4	4	3	3.75
WB3	4	4	4	4	4.00

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The expert evaluation indicates that all indicators achieved average scores above 3.70, suggesting a high level of conceptual clarity and theoretical relevance. Minor wording adjustments were implemented for two indicators to improve semantic precision before the final data collection stage.

Annex C. Measurement Scales

The following section presents the final version of the questionnaire used to measure the constructs included in the structural equation model.

Instructions

Please indicate the extent to which you agree with each statement using the following scale:

1 — Strongly Disagree
2 — Disagree
3 — Neutral
4 — Agree
5 — Strongly Agree

Artificial Intelligence Adoption (AI)

1. AI1: I frequently use systems that incorporate artificial intelligence.
2. AI2: Artificial intelligence tools are integrated into my daily digital activities.
3. AI3: I rely on intelligent technologies to perform routine tasks.

Perceived AI Benefits (PB)

4. PB1: Artificial intelligence improves the efficiency of my daily activities.
5. PB2: AI systems help me make better decisions.
6. PB3: Artificial intelligence technologies provide useful solutions in my daily life.

Life Satisfaction (LS)

7. LS1: I am satisfied with the overall conditions of my life.
8. LS2: My daily activities provide me with a sense of accomplishment.
9. LS3: I feel satisfied with the direction my life is taking.

Well-Being (WB)

10. WB1: I generally feel emotionally balanced in my daily life.
11. WB2: I experience a sense of well-being in my everyday activities.
12. WB3: I feel positive about my personal and social life.

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