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Artificial Intelligence Influences Intelligent Automation in Tourism: A Mediating Role of Internet of Things and Environmental, Social, and Governance Investment

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Intelligent automation in travel and tourism is likely to grow in the future, which is possible due to advances in artificial intelligence (AI) and associated technologies. Intelligent automation in tourism is a socio-economic activity, which needs an explanation of theory and practice. The study objective is to know the predictive relationship between AI and intelligent automation in tourism with mediating role of the internet of things (IoT), sustainability, facilitating adoption, and environmental, social, and governance (ESG) investment. Designing valuable AI, promoting adoption, analyzing the implications of intelligent automation, and establishing a sustainable future with artificial intelligence are the fundamental constructs of this study. Research in these areas enables a systematic knowledge creation that shows a concentrated effort on the part of the scientific community to ensure the positive uses of intelligent automation in the tourist industry. A quantitative research approach was used to collect and analyze data. A purposive sampling technique was applied, and data were collected from four hundred two ($N = 402$) respondents. The results revealed that AI has a predictive relationship with intelligent automated tourism. Similarly, IoT, sustainability, facilitating adoption, and ESG have influenced tourism. As a conclusion, AI design can improve tourism department if the intelligent automated framework was applied to it.

Keywords: artificial intelligence, automation, tourism, internet of things, ESG investment

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INTRODUCTION

The focus is on artificial intelligence and intelligent automation in tourism. Defining, visualizing, designing, and delivering artificial intelligence (AI) solutions to the travel and tourist business needs proper critical evaluation impossible with intelligent automation (Zhao et al., 2011). AI knows which type of systems can be reliable for the tourism sector and how they could be constructed for future tourists. The problem is that AI systems need high resources and concentration to sustain the structure. For this reason, an intelligent automated system could be developed to improve the tourism sector. There has been an increased recognition that more attention needs to be paid to AI, the internet of things, environmental, social, and governance (ESG), sustainability, adoption, and intelligent automation in the tourism sector. In recent years, AI technology has emerged as a desirable domain for tourism. An understanding of artificial intelligence automation may prove essential in recognizing tourism experiences and tourist observations in the future. The study explains the cause-and-effect relationship of new artificial intelligence technologies. It is a projective influence on intelligent automation tourism, which can sustain ESG criteria—identifying how intelligent automation might improve tourists' knowledge and visitor's trip with the artificial intelligence automated framework. This method attempts to bypass some of the common problems faced by tourists in the past.

A slightly more advanced method has been proposed with the help of artificial intelligence automation, and it may improve the tourism departments and their client's enthusiasm toward trips and travel (Yue et al., 2012). The combination of artificial intelligence is crucial to constructing intelligent automated technologies for the future sustainability of tourism. Multidisciplinary perspectives are working in tourism and its relationship with AI automation, such as psychology, anthropology, behavioral science, business studies, and human–computer interaction (HCI), as well as design research methodologies such as cybernetic thinking (Martelaro and Ju, 2018; Tuomi et al., 2019), speculation technique (Wong, 2018), prototyping (van Allen, 2018), ESG factors for travel and tourism industry (Ionescu et al., 2019), and multidisciplinary approach with artificial intelligent automation that can be helpful to the tourism field (Churchill et al., 2018). Creating unforgettable travel experiences requires a careful choreography of many components based on an in-depth knowledge of the needs of tourists (Tussyadiah, 2014). Designing tourist experiences means considering the entire journey, from planning to post-trip reflection, and focusing on ways to encourage participation and involvement. Explaining AI's role in enhancing, augmenting, or substituting tourist encounters is critical in the context of user experiences (Lindvall et al., 2018). ESG investment in artificial intelligent tourism can be possible with the internet of things (IoT). These factors previously mentioned are helpful for the visitors. The development of criteria for functional AI systems is aided by various desirable behaviors for systems tackling particular concerns and tourist contact points.

Most importantly, the design is critical to determine how intelligent automation affects tourism. AI systems implementation can adjust best tourist locations and social (and physical) structure in the future tourism department. Tourists may be persuaded to visit well-known places through predictive analytics and virtual tourism information. The "automated tourist experiences" can only be conceptualized if research explains the causal relationship between artificial intelligence and intelligent automation in tourism. ESG investment and IoT can make a more sustainable future for tourism. As a result, artificial intelligence thoughts can design intelligent automation tourism environment.

LITERATURE REVIEW

The design of valuable artificial intelligence is focused on finding technology answers to long-standing design issues, such as psychology, cognitive and behavioral sciences as well as information systems that would be used to shed insight on the persistent behavioral problems that tourists display, such as lack of discipline, insufficient attention, or absence of cognition. These challenges should be addressed by requiring AI systems to discourage visitors from making misinformed judgments that result in inadequate practices (Tussyadiah, 2020). For instance, digital nudging (Schneider et al., 2018) and nudge theory aspect involvement (Thaler and Sunstein, 2009) may be used to achieve this goal in the tourism industry (Tussyadiah et al., 2019; Tussyadiah and Miller, 2019). Automated systems may solve issues that need immediate attention to the flow of visitors at a destination and give help then sending push notifications and recommending alternative destinations. In this regard, Fogg (2009) described Captology as a computer technology mediation that is essential to save the environment and maintain social satisfaction, which is persuasive for human beings. Tussyadiah (2017) delineated quantitatively that human–computer interaction may be used as lenses for research, and ESG investors should plan for the implementation (Tung and Law, 2017). Another work exploits the value perceived by the tourist and the attachment to intelligent voice assistants (IVA) and the quality of the human–VAT relationship in the field of hospitality (Loureiro et al., 2021). Online analysis of tourism service consumers supports their policy of continuous improvement, creating a positive impact on customer satisfaction, which ultimately leads to the intention to continue digital platforms (Filieri et al., 2021).

Designing valuable artificial intelligence from a technological standpoint necessitates highlighting the necessity of critical artificial intelligence (Russell et al., 2015; Tadapaneni, 2020). Robustness against requirements, exploits, defects, and cyberattack risks are all factors to consider (He et al., 2019; Luo et al., 2020; Shao et al., 2020; Fan et al., 2021; Khan et al., 2021; Wang et al., 2021). Russell et al. (2015) emphasize the necessity of verification in the form of "correct system design" and also validation with correct system design, which was also argued earlier by Menzies and Pecheur (2005). The first point to be considered is that the AI systems need access to a vast quantity of data; in tourism, these data mainly comprise personal information collected from tourists. ESG criteria should be built to make the most out of data while causing the least amount of intrusion into people's privacy and a feasible environment (Lords, 2018; Sethu, 2019; Tussyadiah et al., 2019). Techniques may address this problem to data anonymization and de-identification in the tourism department (Garfinkel, 2015; Khalila and Ebner, 2016). The second predictive stage focuses on the developers' perspectives, consumers, and the regulators' need to comprehend and justify artificial intelligence for any industry (Lords, 2018; Monroe, 2018). Another area of study should be improving artificial intelligence's technological openness and decreasing prejudice, which is essential for the future. In the third stage, building artificial intelligence with the perspective of IoT to solve security challenges necessitates the development of guidelines to guide behavior in safety-critical circumstances, identify infiltration and possible exploitation, and avoid hazardous occurrences (Russell et al., 2015). Finally, given the autonomy of these systems, research should be performed on how to maintain some meaningful human control. AI autonomy involves putting notions like “human in the loop” or “human on the loop” into action and relationships with social agent (Dautenhahn, 1998; Schirner et al., 2013; Lugrin, 2021; Schoenherr, 2021).

The next step is to make it easier for tourism businesses, workers, and visitors to implement (positive) intelligent automation. The present adoption pattern and prospects and the key drivers and impediments to adoption must all be determined *via* research. Theories and models that evaluate innovation diffusion, acceptability, resistance, use, and ease of service and those that assess innovation diffusion, acceptability, resistance, use, and discontinue of use were previously valuable in this field. Examples are the role of “diffusion innovation theory” (Rogers, 2003, 2003), “theory of reasoned action” (Fishbein and Ajzen, 1975), “theory of planned behavior” (Ajzen, 1991), “the technology adoption model” (TAM; Davis, 1989), “the extended TAM2 model” (Venkatesh and Davis, 2000), “the Unified Theory of Acceptance and Use of Technology” (UTAUT) and UTAUT2 (Venkatesh and Davis, 2000), “and the Unified Theory” (Venkatesh et al., 2003; Venkatesh et al., 2012).

At a personal level, in combination with the drivers and obstacles to general technology adoption, such as simplicity of use, usefulness, and technological self-efficacy, research efforts should be focused on discovering characteristics specific to artificial intelligence, robots, and the IoT that affect the appropriateness of innovation, such as trustworthiness and vulnerability parameters of the ESG investment necessary for the field of tourism. Researchers had argued that if it comes to engaging with robots, there is a certain amount of nervousness in society, which leads to an unfavorable attitude toward robots (Nomura et al., 2006; Nomura et al., 2006). Negative views regarding AI and robots in the news media may increase this mentality. To better comprehend tourist customers’ and staff attitudes toward intelligent robots in tourist service environments, reference theories are underpinning technophobia (Brosnan, 2002) and the gravitational lensing hypothesis (Mori, 2017; Murphy et al., 2019), technological social inclusion (Wang and Wu, 2021). Kurtessis et al. (2017) derived that organizational support theory is management theory, which may help get employee support for intelligent automation in the industry. Consumers’ attitudes and intentions to use intelligent devices have been measured (Tussyadiah and Park, 2018; Lu et al., 2019), while workers’ attitudes and intentions have indeed been measured (Li et al., 2019).

To enable and expedite intelligent automation implementation in tourism, it is necessary to identify variables affecting the acceptance of innovation at an organizational level. Therefore, knowing the limitations of innovation dissemination in organizations can assist in comprehending the constraints to sector acceptance. The management literature has information on principles underpinning organizational adoption and dissemination of innovation (Frambach and Schillewaert, 2002; MacVaugh and Schiavone, 2010; Sun et al., 2020; El-Kassar et al., 2022) as well as transformational leadership (Bass, 1990; Haeruddin et al., 2021), a factor proved in the literature to speed up technology advancement in corporations (Frambach and Schillewaert, 2002; MacVaugh and Schiavone, 2010; El-Kassar et al., 2022). Intelligent automation could be studied to see how it fits into the strategic priorities of commercial and public tourist organizations and the competitiveness conditions throughout the sectors (Rydzik and Kissoon, 2021). ESG investors collaborate with the present government and attempt to stimulate adoption (advocacy, funding), and organizational activities to educate prospective users might then be offered to eliminate obstacles and enhance responsible adoption in the organization (Oyewole, 2021).

To maximize the advantages of intelligent automation in tourism, it is crucial to foresee the spectrum of automation’s good and bad effects on people (tourists, personnel), the industry, and society. The functions and effects of intelligent systems in the tourism department are essential for the future of sustainability (Gretzel, 2011; Gajdošík and Valeri, 2022). However, the study did not concentrate primarily on artificial intelligence. Furthermore, Lin et al. (2011) identified three areas of ethical concern coming from the use of robots: safety and mistakes, law and ethics, and societal consequences. Anticipating service failure due to technical (programming) faults during human–robot contact is an essential part of intelligent machine adoption. As a result, research must focus on ways to reduce the potential of damage through artificially intelligent actors in a variety of service contact scenarios. Psychological effects of human–robot contacts, such as concerns of privacy (monitoring) and data protection, are mandatory for the satisfaction of tourists (Pagallo, 2016; Chatzimichali et al., 2021). On the other hand, there are emotional reactions to the proximity of robot appearance to humans (Walters et al., 2008; Mori, 2017; Akdim et al., 2021) and technostress (Ayyagari et al., 2011; Beltrame and Bobsin, 2021; Tuan, 2021). In a nutshell, societal challenges, safety, privacy consequences, and technostress have crucial influence on the structure and quality of tourist experiences in the future, which make it unsustainable (Beltrame and Bobsin, 2021; Chatzimichali et al., 2021; Tuan, 2021).

Another central area of study is the modifications intelligent automation can introduce to the tourism sector, such as alterations to organizational decision-making processes as artificial intelligence substitutes portfolio managers (Javelosa, 2017) and the unintentional effects of AI (-assisted) judgments (Jarrahi, 2018). Likewise, Larivière et al. (2017) described that cooperative decision-making, work allocation, and special scientists can look at the balance of people and then make intelligent systems. Furthermore, again it was conceptualized that automated tourism, accommodation service experience’s creation, and expenditure considering intelligent automation are possible due to artificial intelligence system. The study found that artificial automation could modify the roles of employees and customers in automated intelligent services. Artificial intelligence framework positively influences work performance and an intelligent artificial sustainable system.

The social and economic effects of intelligent automation on the tourist sector, local citizens, and economy bring effectiveness when the degree of hospitality and tourism can become replaced by intelligent machines. In response, intelligent machines can generate valuable earnings, revenue redistribution (disparities), while overcoming gender problems, and total wealth in the tourism sector. In terms of labor, automation raises worries about the loss of skills and knowledge in society as a result of over-reliance on technology, as well as the possibility of a future jobless society (Lin et al., 2011; Chessell, 2018; Pham et al., 2018; Samuels, 2021). Additional implications of intelligent machine progress had already been questioned in the specific situation of technological singularity, a concept in which technological progress would become challenging to control and unrecoverable, and artificial intelligence surpasses human intelligence, resulting in the extinction of human society (Eden et al., 2012; Roli et al., 2021). The same may be said for evaluating social effects, particularly guest–host relationships and local support for tourist growth. Approaches such as future (for example, visualizing futures) and future-making (Hajer and Pelzer, 2018; Szántó, 2018; Szántó et al., 2020) could be used in addition to machine learning approaches to increase prediction and forecasting efficiency in the industry (Ahmed et al., 2010; Kamolov et al., 2021).

Ideally, academic efforts can discover how intelligent automation may assist the tourist industry in becoming more futureproof. After learning about the many advantages and issues that may arise from implementing intelligent automation, the next step is to recognize the various ways of minimizing adverse effects and maximizing the benefits of automation in tourism. The principle of sustainability changeover (Markard et al., 2012; Safarzyńska et al., 2012; Turnheim et al., 2015; Yue et al., 2021; Bauer et al., 2022) is crucial for guiding exploration in this area, particularly in identifying how AI systems could perhaps be used to structure transition mechanisms to sustainable progress across tourism. Government policy is critical in addressing the profession's and society's possible negative consequences of intelligent automation. Policy interventions via education and training programs to address skills shortages in AI-related occupations or minimize capacity loss due to automation dependency, encouragement to promote labor-intensive sectors like hospitality, and a guaranteed basic income to improvement in primary mass jobless due to automation are just a few examples. Furthermore, tourism organizations and other stakeholders may utilize a variety of intervention tactics to encourage visitors and staff to engage in responsible conduct (Navío-Marco et al., 2018; Xiang, 2018).

Intelligent automation can significantly change tourism in the not-too-distant future, reducing the necessity for human, face-to-face contact between visitors and inhabitants (tourism staff) even more than it now does. Lack of socialization may result in the loss of shared values necessary for structured social life, including care for others' well-being and environmental preservation such as ESG criteria (Han et al., 2019; Bao et al., 2020; Yue et al., 2020; Zhumadillayeva et al., 2020; Pan and Yue, 2021). The task at hand is to determine how much artificial intelligence and robotics can contribute to solving these emergent problems. As individuals become more reliant on virtual advisers and robots to help them manage their everyday lives and travel requirements, we must fundamentally transform our perspective of intelligent agents from simple tools to vast and complicated social players. Humans can be guided, informed, and mentored by computational systems that raise public awareness of physical and biological thresholds and human well-being while boosting answerable and resource-efficient behavior. Humans and the environment hold the key to efficient human–robot interaction for a sustainable society. As a result, more research is needed to figure out how to humanize humans in the age of intelligent machines and add value to the expansion of robotics (Kopacek and Hersh, 2015; Fusté-Forné and Jamal, 2021). Also, exploration can be focused on developing scientific, cultural, and technological instruments to support and stimulate current trends for the progress of society and people, as well as to assist in avoiding the exploitation, mistreatment, indifference, and misuse of artificial intelligence and robots (Kopacek and Hersh, 2015; Fusté-Forné and Jamal, 2021). The fundamentals of robotics must also be considered when developing specifications for robust artificial intelligence, establishing a feedback loop that leads to the development of beneficial AI (Tussyadiah, 2020).

Research Method

The study used a positivistic and quantitative approach to explain the relationship between artificial intelligence, ESG, IoT, creating a sustainable future, facilitating adoption, tourism, and intelligent automation in tourism. Quantitative research knows the facts objectively (Creswell, 2010). The rationale behind this approach was to understand the projective association between artificial intelligence, ESG, and artificial automation in tourism.

The study's main objective was to highlight the importance of artificial intelligence, ESG, IoT, facilitating adoption, creating a sustainable future, and intelligent automation tourism of China. Ethical considerations and consent forms were initially filled, followed by the COVID-19 standard operating procedure (SOP). However, the study did not mention the specific tourist place due to ethical issues, because respondents did not disclose their anonymity.

Moreover, the working hypotheses are correlated with the objectives of the study, respectively:

1) The first hypothesis is that artificial intelligence has actively contributed in recent years to the intelligent automation of services in the tourism sector;

The paper uses an explanatory method to explain the theory and co-relationship with quantitative results. Second, quantitative data were collected through a questionnaire, and the research has adapted items from the previous empirical literature review. The self-administered questionnaire was distributed with the help of local language researchers to take reliable and valid data from the respondents.

2) The second working hypothesis is the predictability of tourist services by using models of structural equations;

The paper analyzes the predictive impact of artificial intelligence on intelligent automation in tourism with mediating influence of ESG, IoT, facilitating adoption, and creating a sustainable future with structural equation modeling (SEM), which is a gap in the literature. The initial model and model fit were measured and employed in the existing artificial intelligence automation tourism situation. The final decision was taken on the modified model fit, and its coefficient of determination was used for prediction.

3) The third hypothesis is related to the direct interdependent relationship between artificial intelligence and intelligent automation in tourism.

The paper developed a linear model to study the artificial intelligence relationship and its dependency on intelligent automation in tourism. Data were collected from five popular tourist places in China. Different researchers developed scales, and we adapted a scale from previously valid and reliable dimensions, factors, indicators, and elements, which were identified in the existing literature. The study nature was quantitative, and accurate and reliable items are always demanded. For instance, the study used seven (7) different types of scale, such as the internet of things (IoT, 8 items and the study just selected 4 items that have good Cronbach alpha value and we retained in our research) that Krishna and Verma (2016) and Vašíček et al. (2017) adapted, "artificial intelligence" (AI = 5 items), "creating a sustainable future" (CSF = 6 items), "intelligent automation tourism" (IAT = 6 items), and "facilitating adoption" (FA = 8 items) indicators by Tussyadiah (2020), "tourism impact scale" (T = 6 items) (Ap and Crompton, 1998), and "ESG measurement scale" (ESG = 8 items)" indicators adapted from Sultana et al. (2018). Reliability and validity are the essential measurements of the questionnaire, and this paper collected one hundred-two (102) pilot tests to ensure reliability and validity of the scale. The concepts were converted to the variables, and seven (7) indicators were chosen for the artificial intelligence automation in tourism in the tourist places of China. The study counters these indicators with a non-probability purposive sampling technique with N = 411 sample size through ("G*Power") "software", which is shown in **Figures 1, 2** and **Eq. 1**. (Faul et al., 2007). In this regard, N = 402 have given the responses regarding artificial intelligence automation of tourism, which were proceeded for the data analysis phase. Similarly, the data were collected from the 402 tourists and their tourism department employees. **Equation 1** of the sample size is given:

$$\begin{aligned}
&\gamma = X\beta + \varepsilon \\
&\mathrm{X} = (1X_1,\ X_{2......}X_m)\ and\ N \times (m+1,\ matrix\ = X_{\boldsymbol{i}}) \\
&\beta \text{ of length } = (m+1) \\
&\varepsilon \text{ of length N} = (\varepsilon \mathrm{i}\ \sim\ \mathrm{N}(0,\ \sigma)
\end{aligned} \tag{1}$$

Suppose that...

$$\text{H0: } R^2Y.B = 0$$

$$\text{H1: } R^2Y.B > 0.$$

The effect size and its equation for the sample size are given:

$$f^2 = \frac{R^2\,Y.B}{1 - R^2\,Y.B}$$

$$R^2\,Y.B = \frac{f^2}{2 + f^2}$$

The sample size has seven (7) predictors and a similar noncentrality parameter (λ = 20.550). The value of "Critical F" is important for measuring the sample, and it was 2.032 with numerator df (7). Denominator df was count 403, and effect size f square was 0.05. Similarly, power (1 − β = 0.93) is measured for the sample size, and actual power was 0.930. In conclusion, the study's sample size was derived (N = 411) and 402 respondents filled questionnaire.

The researchers took help from the formula of "F test linear multiple regression: fixed model, R^2 deviation of predictors" and followed the COVID-19 SOPs. Furthermore, Statistical Package for Social Sciences (version 21), AMOS and SEM, were used to measure the initial model and model fit for the paper conclusion. This empirical paper has tested two models to project the tourism and intelligence automation tourism among tourist and employees. For instance, the initial model has seven (7) constructs, and their values of RMSEA and SRMR were higher than cutoff points such as 0.19 and 0.47, whereas the GFI, CFI, and NNFI values were 0.694, 0.592, and 0.629, lower than the cutoff point, which indicated that there is no ideal fitness present. On the other hand, the χ^2/df value was 10.496, which is also higher than the cutoff point. As a result, the model needs modification, which suggested that SEM and added two covariate control factor, error terms, with the combination of nine (9) indicators for the causal and effect theoretical relationship for an inferential measure of the intelligent automation of tourism among Chinese tourist and tourism department employees. According to the modeling phase, data pre-processing activities are necessary to guarantee that inaccurate, blaring, redundant, and repetitive information are removed from the data. **Equation 2** describes the "sum of squared differences" between the line and the actual data point is minimized, and it is called Alpha squares in the multiple regressions and with several predictors.

$$\begin{aligned}
&Otcome\ i = (\text{model}) + \text{error}\ i \\
&Y = (b_0 + b_1\,X_{i1}\ +\ b_0 + b_2\,X_{i2}\ + ...\ b_0 + b_n\,X_n\ ) +\ \varepsilon_i
\end{aligned} \tag{2}$$

Similarly, the SEM measures the level of dependency in the linear equation model, which leads to the structural modeling in applied statistics. **Equation 3** is the basic formula of the SEM.

$$\begin{aligned}
&C(\alpha.\alpha) = [N - r]\left[\sum_{g-1}^{G} \frac{(N)^{g\,f\left(\mu^g, \sum g, x^{(g)}, S^{(g)}\right)}}{N}\right] = [N - r]F(\alpha.\alpha) \\
&\text{fkl}\left(\mu^g \sum (g) x^{(g)} S^{(g)}\right) \\
&\quad = \log\left[\sum g\right] + tr\left(S^{(g)} \sum (g-1) + \left(x^{(g)} - \mu^g\right) \sum (g-1) \left(x^{(g)} - \mu^g\right)\right) \\
&c = \left(N^1 - 1\right)F^{(1)} = (N - 1)F. \\
&C = \sum_{g=1}^{(G)} N^{(g)} F^{(g)} = FN.
\end{aligned} \tag{3}$$

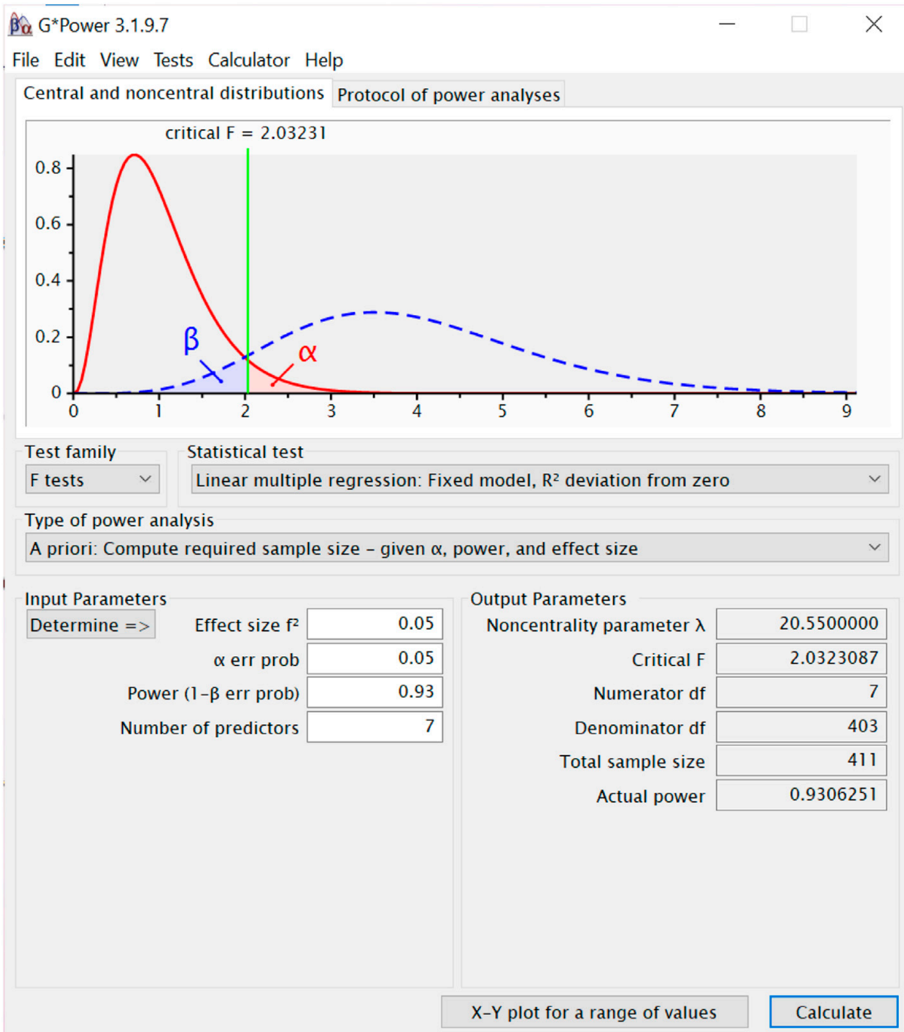

FIGURE 1 | Central and Noncentral Distribution.

Furthermore, data were ready for the normal distribution, and all the outliers were removed from the data, which is the basic assumption of a regression equation. The final training dataset was evaluated with the help of these aforementioned equations and further applied bootstrapping technique to the model fit (second model) for accurate results and future efficient prediction for intelligent automation in the tourism, which can be beneficial for the ESG criteria.

Data Analysis

This study empirically tests all the indicators with confirmatory measurement factor analysis and derives an equation for each item (statements). The measurement model suggested that construct validity and reliability are perfect, and the model is applicable for the further structural equation evaluation, which is portrayed in **Figure 3**. Moreover, the initial model (first model) and model fit (second model) were measured for the actual prediction of beneficial artificial intelligent automation in tourism department with ESG protocols. Likewise, the initial model was not found with satisfactory results, meaning not a good fit with the **Eq. 2** criteria, and the paper modified the proposed model and added two control variables (respondents' age and education) with covariate paths as well as error term (e1, e5, e6) as covariates to achieve desired results. These added factors evaluate the model statistically significant (**Figures 3**, **5**).

The primary goal of path analysis is to determine any causal relationships among the study variables. SEM is one of the most advanced approaches for determining whether or not a cause-and-effect connection exists between a set of variables (Hair et al., 2014). Notably, the paper differentiated a casual R^2 relationship between the initial model and model fit. It is to be noted that the actual logic of path analysis is to develop a diagram that is clearly connected with arrows, covariate, and show the real causal flow or the real direction of cause-and-effect for future prediction. The beauty of path analysis is that it measures association from the direct path to indirect causal effects, can be estimated simultaneously, and predicts a good model for future issues. So, the path diagram

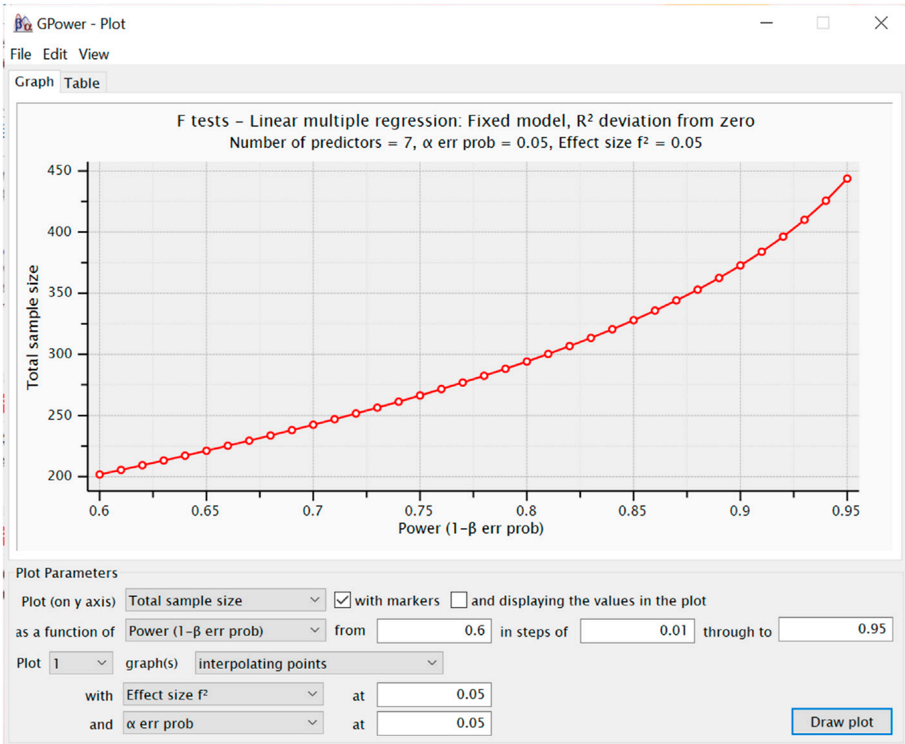

FIGURE 2 | F Tests.

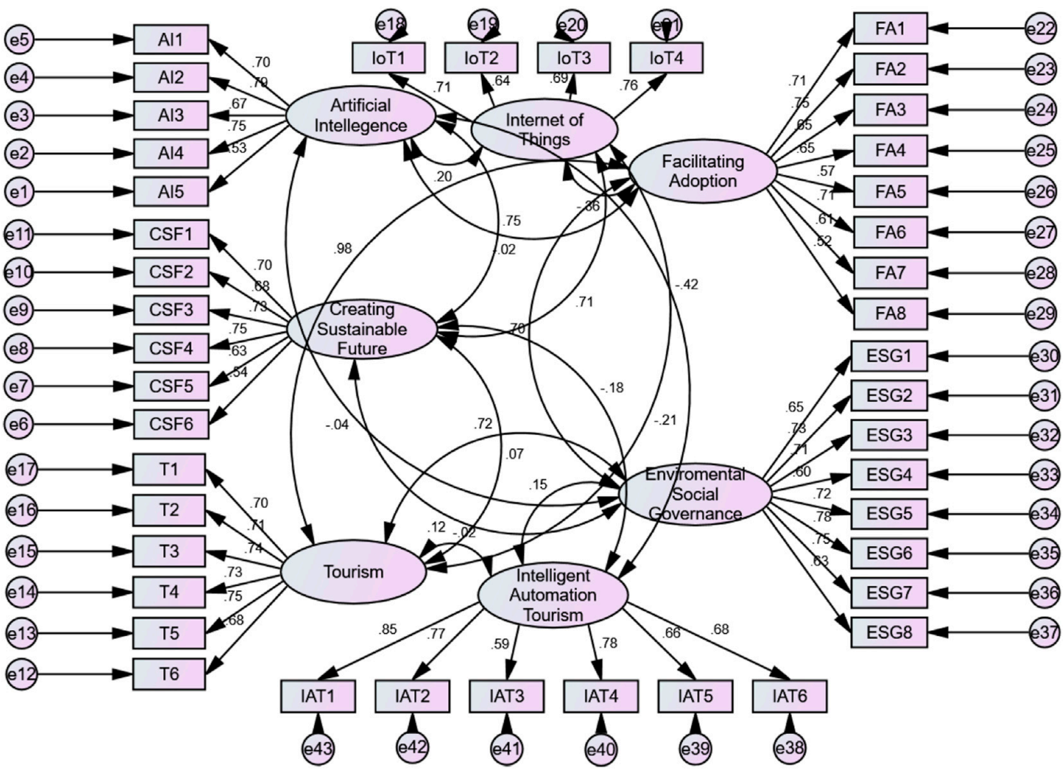

FIGURE 3 | Measurement of the artificial intelligence, intelligence automation tourism, and internet of things (N = 402).

TABLE 1 | Fit indices for artificial intelligence, facilitating adoption, sustainability, ESG investment, intelligent automation tourism, and internet of things among tourists (N = 402).

Model	$\chi^2 df$	χ^2/df	*GFI*	*CFI*	*NNFI*	*RMSEA*	*SRMR*
Initial model	10.496	1.785	694	0.592	0.692	0.476	0.195
Model fit	3.719	1.393	0.936	0.921	0.863	0.086	0.095
$\Delta\chi^2$	6.777	—	—	—	—	—	—

Note: N = 402, *All the changes in χ^2 values are computed relative to model, χ^2 > 0.05, GFI = goodness of fit index, CFI = comparative fit index, NNFI (TLI) = non-normed fit index, RMSEA = root mean square error of approximation, SRMR = standardized root mean square, $\Delta\chi^2$ = chi-square change.*

shows a pictorial illustration of the theoretical explanation of cause-and-effect relationships among a set of variables up to numerical results (ratio and percentages). Agresti and Finlay (1997) concluded that the basic attribute of path analysis is to build direct and indirect causal effects among the set of outcomes and predictors. The use of indirect effects is very beneficial in the derivation of scientific knowledge. An indirect effect is when a variable affects an endogenous indicator over its effects on some other factors or indicators. It is called an indirect effect and is also known as intervening indicator in the subjective model. However, SEM was constructed and applied to evaluate the mediating role of creating sustainable future, facilitating adoption, ESG, and IoT, between artificial intelligence and intelligent automation in tourism. The exhibition of the initial model and model fit are shown in **Table 1**.

The statistical equation for the SEM in the context of intelligent automation in tourism was introduced and the equation derived the CMIN values, which is shown in the formula covariance-based model **Eq. 4**.

$$
\begin{aligned}
&C\,(\alpha.\alpha) = [N-r]\left[\sum_{g-1}^{G}\frac{(N)^{g\,f\left(\mu^{g},\sum g,x^{(g)},S^{(g)}\right)}}{N}\right] = [N-r]F(\alpha.\alpha)\\
&\mathrm{fkl}\left(\mu^{g}\sum(g)x^{(g)}S^{(g)}\right) = \log\left[\sum g\right] + tr\left(S^{(g)}\sum{}^{(g-1)+\left(x^{(g)}-\mu^{g}\right)}\sum{}^{(g-1)\,\left(x^{(g)}-\mu^{g}\right)}\right)\\
&c = \left(N^{1}-1\right)F^{(1)} = (N-1)F.\\
&\mathrm{C} = \sum_{g=1}^{(G)} N^{(g)}F^{(g)} = FN.\\
&(D1)CMIN\ Initial\ Model = 10.496\\
&CMIN\ Model\ Fit = 3.719\\
&\Delta\chi^{2} = 10.496 - 3.719 = 6.777\\
&D2\ fml\left(\mu^{g}\sum(g)x^{(g)}S^{(g)}\right) = fkl\left(\mu^{g}\sum(g)x^{(g)}S^{(g)}\right) - fkl\left(\mu^{g}\sum(g)x^{(g)}S^{(g)}\right)\\
&= \log\left[\sum g\right] + tr\left(s^{g}\sum(g-1) + \left(x^{(g)-}\mu^{(g)}\right)\sum(g-1)\left(x^{(g)}-\mu^{(g)}\right)\right.\\
&CMIN\ Initial\ Model = \chi^{2}/df = 1.785\\
&CMIN\ Model\ fit = \chi^{2}/df = 1.393
\end{aligned}
\tag{4}
$$

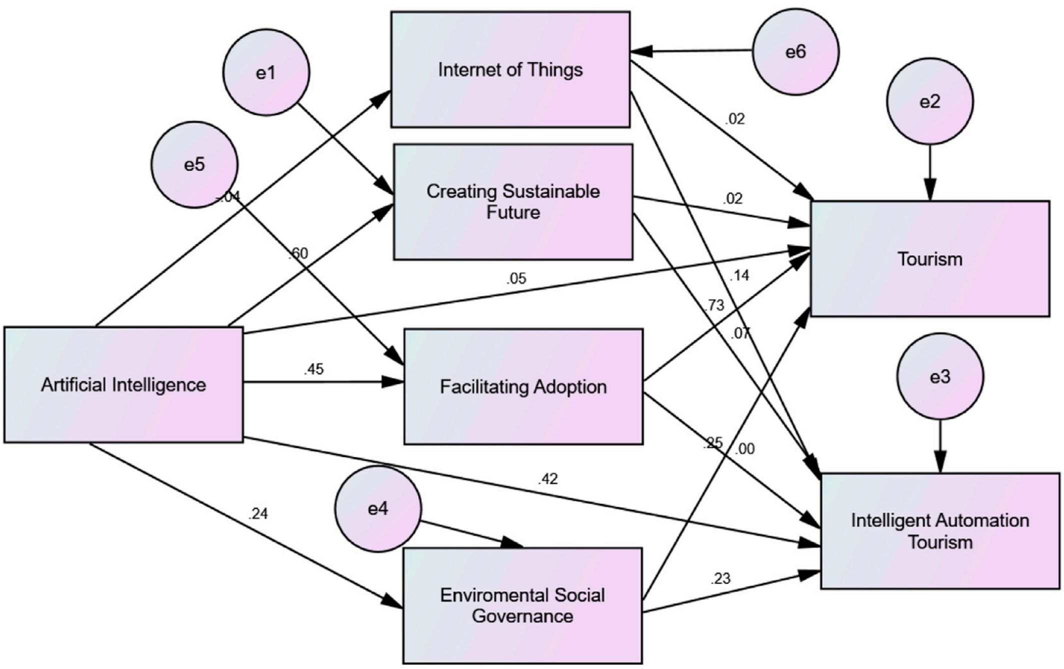

FIGURE 4 | Empirical results from a complex multivariate initial model representation standardized regression coefficient for intelligent automation in tourism (N = 402). Note: a complex multivariate model of five endogenous constructs and two exogenous indicators. Completely standardized maximum likelihood parameter estimate for intelligent automation in tourism among tourists and employees.

The fit indices indicated for designing beneficial artificial intelligence, intelligent automation tourism, sustainability, facilitating adoption IoT, and tourism are shown in **Table 1**. Absolute fit for model fit was χ^2 (12,402) = 3.719, $p < 0.001$. The fit indices were considered to indicate the good fit of the data with the tested model and the study analyzed the model fit in two key steps. In step 1 and step 2, the indices' absolute and relative fit (GFI, CFI, NNFI, RMSEA, SRMR) were compared. Because the χ^2 test of absolute model fit is sensitive to sample size and number of parameters, investigators often turn to various descriptive fit statistics to assess the model's overall fit in data. The following equation mathematically measures the absolute and relative fit (**Eq. 5**):

$$
\begin{aligned}
&GFI = 1 - \frac{\dot{F}}{\dot{F}_b} \\
&f\Big(\big(\textstyle\sum(g), s^{(g)}\big) = \frac{1}{2} tr\big[K^{(g-1)}\big(x^{(g)} - \textstyle\sum(g-1)\big)\big]\Big)2. \\
&Model\ fit\ value\ of\ GFI = .936 \\
&CFI = 1 - \frac{\max\left(\hat{C} - d, 0\right)}{\max\left(\hat{C}_b - d_b, 0\right)} = 1\frac{NCP}{NCP_b} \\
&RNI = 1 - \frac{\hat{C} - d}{\hat{C}_b - d_b} \\
&Model\ fit\ value\ of\ CFI = .921 \\
&TLI = 1 - \frac{\frac{\hat{C}_b}{d_b} - \frac{\hat{C}}{d}}{\frac{\hat{C}_b}{d_b} - 1} \\
&Model\ fit\ value\ of\ TLI = .863 \\
&SRMR = \sqrt{\sum_{g-1}^{G}, \left\{ \sum_{i-1}^{pR}, \sum_{j-1}^{j \le i}, \left(\check{s}^{gij}- ; \sigma^{(gij)}\right) \right\} / \sum_{g-1}^{G} p*(g)}. \\
&Model\ fit\ value\ of\ SRMR = .095 \\
&Population\ RMSEA = \sqrt{\frac{F}{\frac{0}{d}}} \\
&Estimated\ RMSEA = \sqrt{\frac{F}{\frac{0}{d}}} \\
&LO\,90 = \sqrt{\frac{\delta L/n}{d}} \\
&HI\,90 = \sqrt{\frac{\delta U/n}{d}} \\
&RMSEA = .086
\end{aligned}
\tag{5}
$$

Hu and Bentler (1999) measured that χ^2/df in between 1 and 3 RMSEA and SRMR values should be less than 0.08 and CFI, TLI, or NNFI and GFI values usually higher than 0.9 are considered as a good value when it becomes 0.9 ≤ 0.8 then allowable in some cases. Likewise, RMSEA and SRMR for the initial model were 0.47 and 0.19, whereas the GFI, CFI, and NNFI values were 0.69, 0.59, and 0.69, respectively, while the other side χ^2/df value was 1.785 in the above (**Table 1**). The fitted model of the study was fit according to the descriptive measure of fit because the p values were <0.05). Furthermore, the model modification process started as suggested by the modification indices for the intelligent automation tourism. Modification indices followed up some of the variance and covariances between errors in terms of artificial intelligent automation in tourism indicators because some of the elements were similar in content and context. According to Tomás et al. (1999), the covariance between error terms in survey-based research can legitimately draw the variance. The criteria of modification indices for error covariance should be at least 4.0 (Byrne, 2016). Moreover, the study drew the covariance, and the "chi-square Chang" was greater than 6.777 in the modification process. All the non-significant paths were removed in step 2 of the model and added some covariance paths. After that, the indices of absolute and relative fit (GFI, CFI, NNFI, and RMSEA) were again compared and calculated in that stage. The RMSEA and SRMR for the model fit after drawing covariance and removal of insignificant paths were discarded; the results of RMSEA and SRMR (0.08 and 0.09, respectively) were counted since the GFI, CFI, and NNFI values were 0.93, 0.92, and 0.86, respectively, while χ^2/df was 1.393. It means finding the difference between the proposed model and the saturated model. Now it was the perfect model for the projection of the intelligent automated feature in the tourism when mediation model was added. In conclusion, the model was fit, and the modification process does not allow the data to further modify the model (**Figure 4** and **Figure 5**).

Figure 5 also suggested that the path coefficient was significant because p values were <0.05. Now which path coefficient was considerably significant, and which one was not significant, the arrows of the path had explained in numbers. As a result, the mediation model measure that IoT, tourism sustainability, facilitating adoption, and ESG investment mediate the relationship between artificial intelligence designing and tourism, and intelligent automated tourism with beta values (CSF = β = 0.55, IoT = β = 0.03, FA = β = 0.40, ESG = β = 0.25). Likewise, artificial intelligence directly influences tourism with a positive path coefficient (AI = β = 0.04, p > 0.05), and artificial intelligence directly influences intelligent automated tourism with a positive path coefficient (IAT = β = 0.41, p < 0.05). The data concluded that creating sustainability was a strong coefficient between artificial intelligence when applied the intelligent automated tourism. Likewise, artificial intelligence brings positive change in the tourism with the help of IoT, ESG policy, sustainable factor, and different facilities in the tourism department. Artificial intelligence brings improvement in the tourism and intelligent automated tourism (**Figure 5**).

The study used bootstrapping technique for the sample enlargement in the model fit and estimates to be analyzed the direct and indirect effects on study variables. For example, artificial intelligence has a direct effect on IoT, sustainability, facilitating adoption, ESG policy as well as indirectly effect on

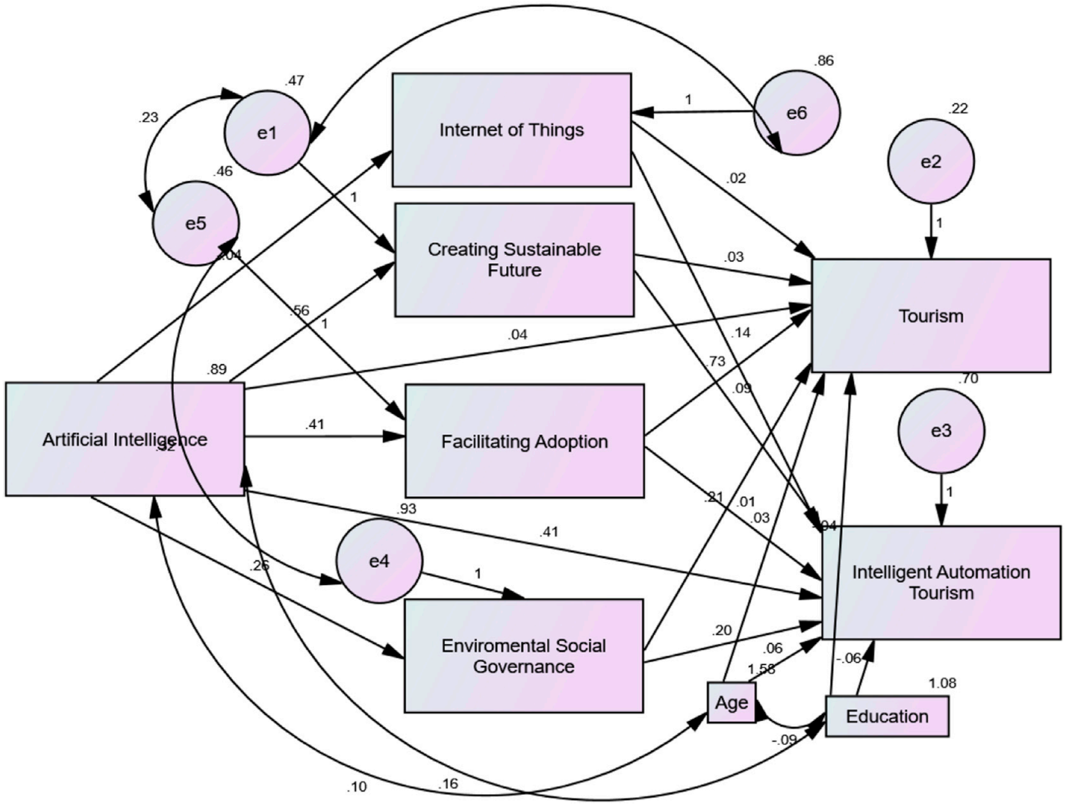

FIGURE 5 | Empirical results from a complex multivariate model representation standardized regression coefficient for intelligent automation in tourism among tourists (*N* = 402). Note: a complex multivariate model of five endogenous constructs and two exogenous indicators along with two control variables. Completely standardized maximum likelihood parameter estimate for the artificial intelligent automation in tourism among tourists and employees.

tourism and intelligent automation in tourism. Similarly, Valeri and VanderWeele (2013) suggested that five thousand (5,000) bootstrapped sample is reliable and valid in the linear multiple paths especially for the SEM analyzed data.

The research hypothesized that artificial intelligence design has beneficial influence on the tourism and intelligent automation tourism with mediating role of sustainability, IoT, adoption, and ESG policy. Likewise, the results of direct effects revealed that artificial intelligence design is a highly significant and positive predictor for tourism as well as a significant positive predictor for intelligent automation in tourism, whereas artificial intelligence design was a significantly positive predictor for IoT while on another side it was found to be a positive significant predictor for facilitating adoption. Furthermore, artificial intelligence was found to be a cause for ESG while also directly affecting the intelligent automation in tourism. The data concluded that artificial intelligence could increase intelligent automation in tourism with the help of ESG, IoT, sustainability, and facilities adoption (**Table 2**).

The aforementioned results in **Table 3** revealed indirect effects of internet of things between artificial intelligence and tourism; it was found to be a highly projective mediator for the overall model. Similarly, internet of things model was found to be a positive mediator for artificial intelligence and intelligent automation tourism. As a result, creating sustainability was found to be an insignificant indirect predictor between artificial intelligence, tourism, and intelligent automation tourism. Similarly, facilitating adoption was a positive indirect significant predictor between artificial intelligence and tourism as well as a positive predictor for intelligent automation tourism. Lastly, ESG was found to be a positive significant predictor for tourism and intelligent automation tourism.

The model fit equation revealed that seven hypotheses were rejected, and all the proposed hypotheses were accepted, as artificial intelligence design predicts tourism and artificial automation tourism. Furthermore, measurement and structural model is showing significant and insignificant paths in **Table 4**.

DISCUSSION

The techniques proposed can be generalized to any tourism sector and the current study found that artificial intelligence brings development in the tourism as well as intelligent automation is beneficial for it. In this context, Ivanov and Webster (2019) delineated that artificial intelligence automation predicts and influences the automated future of travel and tourism. Intelligent automation has begun to infiltrate the world tourist

TABLE 2 | Standardized estimates of direct effects for the paths of intelligent automation in tourism (*N* = 402).

Variables	IoT		CSF		FA		ESG		Tourism		IAT	
	β	S.E	β	S.E	β	S.E	β	S.E	β	S.E	β	S.E
Artificial Intelligence	0.03	0.04	0.55***	0.03	0.40***	0.03	0.25***	0.05	0.04	0.03	0.41***	0.06

*p< 0.05, **p< 0.01, ***p< 0.001. *Note: CSF = creating sustainability future; FA = facilitating adoption; ESG=environmental, social, governance; IoT= internet of things; IAT = intelligent automation in tourism.*

TABLE 3 | Standardized estimates of indirect effects of the paths for intelligent automation in tourism (*N* = 402).

Variables	Tourism			Intelligent automation in tourism		
	β	SE	CR	β	SE	CR
Artificial intelligence						
IoT	0.016	0.031	0.530	0.138***	0.054	2.539
CSF	0.028	0.050	0.550	0.086	0.089	0.965
FA	0.728***	0.052	14.117	0.010	0.091	0.114
ESG	0.208***	0.032	6.852	0.205***	0.054	3.822

*p < 0.05, **p < 0.01, ***p < 0.001. Note: *CSF = creating sustainability future; FA = facilitating adoption; ESG=environmental, social, governance, IoT= internet of things.*

TABLE 4 | Hypothetical paths for artificial intelligence and intelligent automation in tourism (*N* = 402).

Hypotheses	Direction	Paths	Estimate	SE	CR	*p*	Label
FA	←	AI	0.408	0.036	11.333	***	Sig
CSF	←	AI	0.559	0.036	15.426	***	Sig
IoT	←	AI	0.037	0.049	0.752	0.452	Insig
ESG	←	AI	0.257	0.051	5.044	***	Sig
IAT	←	AI	0.414	0.061	6.816	***	Sig
IAT	←	ESG	0.205	0.054	3.822	***	Sig
Tourism	←	CSF	0.028	0.05	0.55	0.582	Insig
Tourism	←	FA	0.728	0.052	14.117	***	Sig
IAT	←	FA	0.01	0.091	0.114	0.910	Insig
Tourism	←	AI	0.04	0.034	1.154	0.249	Insig
Tourism	←	IoT	0.016	0.031	0.53	0.596	Insig
Tourism	←	ESG	0.208	0.03	6.852	***	Sig
IAT	←	CSF	0.086	0.089	0.965	0.334	Insig
IAT	←	IoT	0.138	0.054	2.539	0.011	Sig

*p < 0.05, **p < 0.01, ***p < 0.001. *Note: CSF = creating sustainability future; FA = facilitating adoption; ESG=environmental, social, governance; IoT= internet of things; IAT = intelligent automation tourism.*

practices. The technical side of intelligent systems, meaning how to design better, more effective artificial intelligence for service delivery, has dominated research on intelligent automation, particularly automation applied to the services sectors (Pinillos et al., 2016; Jabeen et al., 2021). This is mainly due to the virtuous artificial intelligence exploration and innovation process. Given dynamic efficiency, artificial intelligence is projected to have a substantial beneficial influence on the economy, and it is quickly establishing one of the most critical sectors in the economic plan of the world's most industrialized countries (Rao, 2017; Dutton, 2018; Yigitcanlar et al., 2021). As a result, empirical research is committed to initiate what might help developed countries gain traction in the race to achieve the next major accomplishment in AI and intelligent robots. The more funding accessible to spend in technical innovation, the quicker artificial intelligence technology improves (Russell et al., 2015). Likewise, Formosa (2021) defined that artificial intelligence has a relationship with social and human robotics autonomy.

Artificial intelligence (AI) has permeated many organizational processes, raising concerns that clever robots could soon be able to make decisions instead of many individuals. This study analyzes how humans and AI might support each other to incorporate decision-making processes that are generally characterized by unpredictability, uncertainty, and ambiguity, to give a more proactive and realistic viewpoint (Jarrahi, 2018). The current study delineated that ESG was found to be a positive significant predictor for tourism and intelligent automation tourism, which is countering unpredictability, uncertainty, and ambiguity among individuals.

The potential applications of artificial intelligent automation have been widely described in literature. For instance, intelligent automation inquiry in the social sciences is underperforming, which is necessary given the significance of intelligent automation for the mechanisms underpinning social interactions and controlling the community. The majority of research has focused on the socially responsible (and legal) attributes of artificial intelligence and its application (Gurkaynak et al., 2016; Nawi et al., 2021). Furthermore, Huang and Rust (2018) have given prediction about possible future consequences for the social evolution of task and competencies. Intelligent automation design is the best facilitator in the adaptation process (Colby et al., 2016; Colby et al., 2016; Huang and Rust, 2018; Jarrahi, 2018). The social science components of intelligent automation and the technological ones must be prioritized in development of human beings (Russell et al., 2015). In this respect, the study concluded that artificial intelligence is a good predictor for bringing sustainability in the tourism sector and intelligent automation tourism is possible in the future.

The limitations of the study are that, for example, the research of intelligent automation in the social sciences is weak, which is necessary given the importance of intelligent automation for the mechanisms underlying social interactions and community control. Moreover, we intend to continue such research so that we can also contribute to intelligent automation in the social sciences, which would make it especially possible in the scientific field of tourism to be able to be automated through artificial intelligence.

CONCLUSION

In summary, scientific technique has demonstrated high-quality results for the intelligent automation tourism with sustainable environmental and social governance. The idea started from the broad research agenda and then systematically constructed knowledge in the area of artificial intelligence perspective, and its relationship with intelligent automation tourism, as well as conducting robust scientific research to advise policy measures and efforts from diverse stakeholder groups, such as governments and tourism organizations, to confirm the answerable adoption of intelligent automation in tourism. The scientific analysis proposes multiple survey preferences based on key scientific inquiries about artificial intelligence, associated automated technology, and their implementations in tourism. However, constructing beneficial artificial intelligence, facilitating adoption, examining the implications of intelligent automation, and establishing a sustainable vision with the help of ESG criteria could be a good framework for the tourism sector. The outcome of predictive model leads to the conclusion that artificial intelligence design can improve tourism department if the intelligent automated framework was applied to it. This is because artificial intelligence, internet of things, facilitation adoption, and sustainable ESG had a predictive association found with intelligent automation in tourism.

Contributions

The main achievements, including contributions, may be summarized as follows:

- Artificial intelligence and intelligent automation framework provide an advancement of state-of-the-art for the tourism sector.
- As a social phenomenon and an economic activity, tourism has to be shaped in the future, and this study provides a framework for future research in the field of AI, robotics, IoT, ESG, and intelligent automation in tourism.
- Policymakers should follow artificial intelligence professionals and specialists for intelligent automation in tourism. Afterwards, ESG criteria framework for the future of intelligent automation in the tourism department can positively have an effect.
- It is recommended that artificial intelligence should improve the tourism sector, which positively influences the environment of intelligent automated tourism.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

Conceptualization: LT, WY, and OM. Methodology: LT, WY, and OM. Software: OM. Validation: LT and WY. Writing—original draft preparation: OM and WY. Writing—review and editing: LT and WY. Funding acquisition: OM.

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