The Role of Institutional and Self in the Formation of Trust in Artificial Intelligence Technologies

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Abstract

Purpose – The deployment of artificial intelligence (AI) technologies in travel and tourism has received much attention in the wake of the pandemic. While societal adoption of AI has accelerated, it also raises some trust challenges. Literature on trust in AI is scant, especially regarding the vulnerabilities faced by different stakeholders to inform policy and practice. This work proposes a framework to understand the use of AI technologies from the perspectives of institutional and the self to understand the formation of trust in the mandated use of AI-based technologies in travelers.

Design/methodology/approach – An empirical investigation using PLS-SEM was employed on responses from 209 users. This paper considered factors related to the self (perceptions of self-threat, privacy empowerment, trust propensity) and institution (regulatory protection, corporate privacy responsibility) to understand the formation of trust in AI use for travelers.

Findings – Results showed that self-threat, trust propensity, and regulatory protection influences trust in users on artificial intelligence use. Privacy empowerment and corporate responsibility do not.

Originality – Insights from past studies on AI in travel and tourism are limited. This study advances current literature on affordance and reactance theories to provide a better understanding of what makes travelers trust the mandated use of artificial intelligence technologies. This work also demonstrates the paradoxical effects of self and institution on technologies and their relationship to trust. For practice, we offer insights for enhancing adoption via developing trust.

Keywords: Artificial Intelligence, Trust, Self-Threat, Corporate Privacy Responsibility, Regulatory Protection

Introduction

The use of artificial intelligence (AI) in businesses processes, the workplace, and society has expanded exponentially and transformed the way people interact (Ågerfalk, 2020; Ameen *et al.*, 2021; Dwivedi *et al.*, 2021a; Mikalef *et al.*, 2022a). Generally, the use of AI helps to create a safer workplace, improves health care, and facilitates access to information and education. For businesses, AI enables the development of innovations and services. The transformative power of AI through its ability to sift through a vast amount of data via connected technologies and high-performance computing to generate new insights of tremendous value have become an integral part of many industries' digital strategy (Raisch and Krakowski, 2021) coupled with a growing discourse on the potential benefits of AI solutions (Duan *et al.*, 2019; Dwivedi *et al.*, 2021a).

In this study, we use the term "AI-tech" as an all-encompassing terminology to refer specifically to the mandated adoption of AI-powered technological tools by the regulatory bodies, agencies, and firms against the backdrop of a crisis (i.e. COVID-19) for community-wide monitoring as an effort to contain the crisis. During the onset of COVID-19, such technologies became instrumental in restarting the economy. Many AI-powered mobile applications were developed resulting from World Health Organization (2021, 2022) guidelines that compelled member states to put in place a surveillance system that is data-based, unambiguous, and privacy-centric as part of the COVID-19 response efforts (Jalabneh *et al.*, 2021). Apart from tracking vaccination statuses and vaccination centers, many other digital entrepreneurial initiatives were also prioritized in response to the pandemic (Modgil *et al.*, 2022; Sharma *et al.*, 2020). An example of such an initiative that is useful in breaking the chain of transmission for the safe resumption of economic and social activities is contact tracing applications (World Health Organization, 2021; 2022). The primary tool for contact tracing is the smart mobile phone and an effective contact tracing system must fulfil the requirements for accuracy, privacy, ubiquity, and data security (Trivedi and Vasisht, 2020). The contact tracing application can be designed depending on various features of the smart mobile phone such as Global Positioning System (GPS), Bluetooth, Wireless Fidelity (Wi-Fi), and so forth, or can be categorized according to its use such as outbreak response, proximity tracing or symptom tracking (World Health Organization, 2021). However, these technologies are not without their limitations. For example, the baseline performance of using Bluetooth-based contact tracing applications as proximity detectors remains unknown. In daily scenarios, when a phone is placed in a carrier, the performance starts to degrade (Hsu, 2020). Further, different countries may employ several contact tracing systems based on absolute location data (e.g. GPS, Wi-Fi logs), relative location data (e.g. Bluetooth), facial recognition technologies, or mobile payment systems (e.g. Alipay, WeChat) (Jalabneh *et al.*, 2021). The same technologies such as facial recognition, mobile payment, digital wallets, metaverse, etc. may also be used simultaneously for contactless retail, travel, tourism, and monitoring climate change (Dwivedi *et al*., 2022a; 2022b; Gaur *et al.*, 2021). The technological tools in the context of this study extend beyond digital contact tracing. Singapore for instance uses facial recognition technology in areas of smart public services and delivery services. Calls for the government to be more accountable for its development and deployment are likely as public awareness matures (Harjani, 2021). The United Nations World Tourism Organization (UNWTO) (2020) had called on tourism-related businesses to be responsible while at the same time prioritizing safety and security as countries embrace the new norm and lifted travel restrictions. This work is motivated by the mandatory adoption and availability of AI-tech or AI-powered tools which include contact-tracing applications, contactless payment solutions, travel technologies such as facial recognition, robot deliveries, or even a robot dog that enforces social distancing to contain the virus' progress.

Despite its promises, AI-tech raises a pressing issue of a balance between its affordances and the concerns it raises. According to Digital Reach's Southeast Asia Digital Contact Tracing report (2020a, 2020b) submitted to the Association of Southeast Asian Nations (ASEAN) Intergovernmental Commission on Human Rights, Singapore, Indonesia, Thailand, Vietnam, Malaysia, and the Philippines adopted surveillance technologies to control the outbreak. The report highlighted concerns in relation to technical vulnerabilities, lack of transparency, and lack of policy enforcement. Technical vulnerabilities refer to ways by which the use of such technologies could compromise users' privacy and personal data as most of the data is stored in a centralized location for authorized access. Data stored in such a manner is vulnerable to misuse, exploitation, or data breach. In Malaysia, the government introduced three applications that were complementary to one another although subsequently some were discontinued. The now-defunct app, Gerak Malaysia launched by the Malaysian Communications and Multimedia Commission was discontinued three months post-operation. What was more crucial was that both the National Security Council and the Ministry of Science, Technology, and Innovation had announced that they had not endorsed the app (Digital Reach, 2020a). The second app MyTrace was announced to be open source, and that data collected would be stored in the phone and anonymized. This app was also subsequently withdrawn. While in Singapore, the released source code of the TraceTogether app was not updated following the software upgrade. Hence, information on data management and security design is limited, as in the case of close-sourced software. The report concluded that the situation is an important lesson on how data is treated in a crisis and in times of emergency. This reveals both a lack of transparency and policy enforcement which raises questions about whether the app can be trusted to protect users' right to privacy. In any case, citizens should not be made to give up certain rights in return for public health.

According to Cheng *et al.* (2021), the use of AI inevitably includes privacy concerns, as personal data is collected *en masse* through contact tracing, face, and voice recognition. The juxtaposition between the merits and challenges of AI use is a critical social predicament. This becomes a crucial predicament in the sharing economy, where technology giants (e.g. Apple, Google, Amazon Web Services) create and consume a tremendous amount of user data between a service user and a supplier. For example, the use of AI-tech for tracking and surveillance (Fahey and Hino, 2020), and facial recognition (Whitelaw *et al.*, 2020), raises privacy compliance concerns. AI-tech that is seemingly problematic could result in public distrust (Tzachor *et al.*, 2020). The long-term effects due to society's reaction to the crisis (Gretzel *et al.*, 2020) are understudied. According to Liang *et al.* (2021), the use of AI is causing "transformational effects" (p. 3) relative to fairness, trust, and ethics, and scholars must understand these effects to develop safeguards against them and be aware of societal issues that cannot be disregarded. Trust is important in human-technology relationships (McKnight *et al.*, 2011), but trust can be taken for granted, or it can be eroded quickly due to technological incompetence on the part of the government or social interactions (Robinson, 2020). Although previous studies considered trust as an antecedent to user adoption behavior, this work accords with that of Cao *et al.* (2018) whose work considered the mechanism of building trust. Specifically, this study aims to investigate the factors that build trust in the use of AI-tech. Moreover, this study considered individuals' propensity to trust technology and its effect on individuals' openness to AI-tech. Further, this study draws from the work of Pitlik and Rode (2017), and considered values related to the personal-independence, beliefs in one's empowerment, and the demand for institution frameworks in line with the protection of rights, rule of law to understand attitudinal trust in AI-tech.

Further, existing studies have not considered the impact of AI on the tourism industry specifically based on the mediation of AI (Tussyadiah, 2020). Research on the mechanisms of AI and how it affects the tourism industry is scarce and, studies on the side effects of AI-tech on public management and those leading to policies are rare (Tuo *et al.*, 2021). There is a dire need to research the adoption of AI in tourism for interactions (Tussyadiah, 2020), the influence of perceived trust (Chi *et al.*, 2020), and human replacement (Yu, 2019). For example, in a study by Akhtar *et al.* (2020), anticipated worry and trust in the government had significant effects on resistance through psychological reactance. User hesitation developed by fear, threats, and avoidance triggered an inherent motivation to restore freedom and resist persuasion. In discussing avenues for research arising from the pandemic, Sein (2020) outlined that affordances of technological solutions can only be actualized by knowing the facilitating conditions and conversion factors to increase the uptake of technologies. One's experiences with the use of technologies in coping with the pandemic yield research and practical implications both for the design and use of the technologies. Sigala (2020) questioned whether familiarity or trialability would increase the adoption of controversial technologies and called for research to help the industry design and implement an operational environment that is human-centered and responsible for societal well-being.

Against this backdrop, this paper explores the explanatory insights derived from affordance and reactance in the use of AI-tech by reviewing the literature on AI-tech in the industry, and the concept of trust, followed by the research model and hypothesis development. The findings are then discussed followed by the theoretical and practical implications.

Literature Review

In this section, we present a review of past work on the key concepts that led to the development of the conceptual model that forms the base of this study.

AI Trust and Trust Building

Trust in technology, as with Tussyadiah *et al.* (2020) is defined as users' expectations that the technology will fulfil its expected responsibilities relative to a goal that the user needs to achieve in a particular setting. Trust is a cognitive construct based on a rational evaluation of trustee and situational features that may also be influenced by effect (Glikson and Woolley, 2020). Factors related to users, technologies, and the environment within which the interactions happen can be considered (Nordheim *et al.*, 2019). In the context of AI, trust is more complex because it is confined to the purpose (Ameen *et al.*, 2021), technology, and brand (Zhang *et al.*, 2019). Dependence on AI raises trust issues among customers due to the need for increasing data (Dwivedi *et al.*, 2021a). Ironically, during an epidemic, AI-tech such as service kiosks and chatbots offer a much-needed shield to tourists without risking their health and safety (Ivanov *et al.*, 2022). Gillath *et al.* (2021) demonstrated that how people feel about AI can be predicted by considering their feelings, thoughts, and behavior (termed *attachment* style). Therefore, enhancing one's feeling of *attachment* security could increase trust in AI. Although their study revealed that the elderly and those less conversant with AI were less prone to trust AI; trust in AI did not correlate to *attachment* avoidance.

We first outline the general formation of initial trust following a typology of trust by McKnight *et al.* (2002, 2006) which is based on trust origin, trust formations, and trust operations that form the basis of this study. The initial trust-building model asserts that initial trust is impacted by cognitive processes such as in-group categorization and stereotyping, and illusions of control. Initial trust is important because parties may willingly or unwillingly extend or withdraw cooperation either with confidence or tension. Two interpersonal trust concepts are predicted: trusting intention and trusting beliefs which are influenced by the disposition to trust or propensity to trust and institutional trust (McKnight and Chervany, 2006). McKnight *et al.* (2011) and Nordheim *et al.* (2019) further examined users' trust propensity in technology as a substantial factor of individual differences. A propensity to trust is a consistent trusting tendency (Tussyadiah *et al.*, 2020); a tendency to trust technology is likely to affect trust in a specific technology (McKnight *et al.*, 2011; Merritt and Ilgen, 2008).

Institutional trust such as general beliefs about a protective environment and safeguards conditions the assurance and normality of situations (Williams and Baláž, 2020).

This study extends present research on trust in tourism (Chen, 2006; Kaushik *et al.,* 2015; Luo and Zhang, 2016; Nunkoo *et al.,* 2012; Ouyang *et al.,* 2017; Park, 2020; Tussyadiah, 2020; Williams and Baláž, 2020) which shed light on trust and its association with other variables.

Affordance and Technology

Gibson's (1977) Theory of Affordances, defined here as "resources or properties that support" emphasizes the relational concept of context-dependent interaction between an individual and the environment (Califf *et al.*, 2020). According to Hellström and Jacob (2017), affordance is not a necessity, but a possibility that depends on circumstances. An affordance is relational meaning possible affordances are usually not known by the individual or designer but can be classified according to information provided by objects, and user perception (Lee *et al.*, 2014). Past research on technological affordances that attempted to identify how users relate to their environment includes policy instruments (Hellström and Jacob, 2017), trust (Lankton *et al.*, 2015), and fundamental rights (Graber, 2020). Research on the use of technology in the context of travelling/tourism has reached a degree of maturity, however, interests have mainly been in the dimensions of consumer adoption of web-based services, social media, or mobile systems (Ukpabi and Karjaluoto, 2017); studies of technologies in governance contexts are relatively rare (Gössling, 2021). For instance, affordances implicate concessions of personal data (e.g. consumer preference and purchase behavior tracking, real-time monitoring of locational data), although affordances are usually taken for granted by consumers. In policy and regulations, affordances are tied to concepts and rules that affect the manner they are perceived. Trust in an object is relational; affordances can probably offer indications about the object's nature that could foster trust (Lankton *et al.*, 2015). Particularly, research on the application and impact of a *new generation of AI* that questions the autonomy of a manipulable and exploitable community is limited (Duan *et al.*, 2019)

Psychological Reactance and Mandated Adoption

Reactance is a cognitive reaction arising from experiencing threats from external stimuli (Kwon and Ahn, 2021). A persuasion that reduces or eliminates freedom induces reactance to restore freedom (Rosenberg and Siegel, 2018) either directly or indirectly, even if the persuasion is in their best interest. This eventually causes the failure of the persuasion. Direct restoration involves carrying out the forbidden act while indirect restorations include detracting from the source of the threat, rebuffing the existence of a threat, or employing a different choice alternative to enhance the feeling of restoration. According to Feng *et al.* (2019) and Rosenberg and Siegal (2018), reactance is discussed by considering the threat to freedom of choice, which provokes reactance, and consequently, restoration of freedom. Many practical examples exist to illustrate the nature and consequences when adoptions are forced (Heidenreich and Talke, 2020). Mandatory adoption describes a situation where a particular institution decided to adopt and implement a technology regardless of user willingness. Mandating the adoption of technologies induces reactions at both cognitive and affective levels (Feng *et al.*, 2019) and cognitive reactions such as perceptions of unfairness (Chang and Wong, 2018) or devaluation of the source's credibility (Feng *et al.*, 2019). When users perceive that their freedom to choose is eliminated, they experience a state of enhanced threat, thereby arousing a reactance. Consequently, users may opt to observe the restrictions, or by derogating or resisting the persuasion (Akhtar *et al.*, 2020). It is important to understand how mandated adoption contexts for implementations that are critical to an organization's success can trigger resistance. According to Font and Hindley (2017), reactance theory can advance the understanding of "why users travel to destinations while under threat" (p. 27) and address problems in service recovery (Tang, 2014).

Corporate Responsibility and Regulatory Protection

Corporate firms hold asymmetric control over consumer data and are inherently expected to properly manage and safeguard the data (Bandara *et al.*, 2021; Lwin *et al.*, 2007). The lack of such efforts creates an environment that leaves consumers vulnerable to threats of breaches. Stakeholder transparency for technology increases the credibility of firms and proactive communication too, has a considerable effect on trust in technology (Hengstler *et al.*, 2016). Consequently, scholars have emphasized the role of regulatory intervention to restore confidence in consumers but the dynamics surrounding threats and their impact on consumers remain unclear (Bandara *et al.*, 2021). The usage of AI-tech raises concerns about governance (Gretzel *et al.*, 2015). Users may develop trust in firms due to their privacy management practices (Martin *et al.*, 2017) or they may develop emotional and cognitive violations over worries about personal data and in turn respond with resentment (Martin *et al.*, 2017). This means AI-tech must operate according to defined standards and approved governance policies.

Self-Threat and Privacy Empowerment

Prior studies presented diverse findings on the acceptance of technologies (Ivanov and Webster, 2019). Users tend to exhibit a positive attitude toward technologies if they perceive the technology is trustworthy, safe, and competent (Kaushik *et al.*, 2015). Hengstler *et al.* (2016) found privacy protection, and operational and data security to be key in promoting trust in performance and consumers prefer to retain control over the use of their data (Manikonda *et al.*, 2018). At times of crisis, authorities are faced with the daunting task of needing to balance between moving fast enough in containment efforts and maintaining public assurance (Tzachor *et al.*, 2020). For instance, the mandated use of tracing apps is the rule; users provide personal information in exchange for service and trust-building is limited (Gretzel *et al.*, 2015). Users who felt an invasion of their privacy responded by taking deflective and defensive behaviors (Lwin *et al.*, 2016) with significantly different consequences (Heidenreich and Talke, 2020).

Research Framework and Hypothesis

Trust in Mandated AI-Tech

While mandated adoption can and will accelerate uptake as soon as possible, it can also completely alter (or negatively affect) user acceptance (Cserdi and Kenesei, 2021). According to Cook (2018), users are fearful and less trusting of technology usage when the usage is imposed upon them without alternative(s). Their study showed that voluntary use of technology including the availability of choices increased informed decision-making and trusted reliance on technology. Choice in technology usage carries greater trust. Mandated use, on the other hand, can result in confusion, misuse, and rejection by people with rudimentary technology skills. And in situations where mandatory use becomes the norm, the lack of trusted acceptance of a technology depends on the ability to gain reassurance in the mandated usage, not just a lack of choice. The motivations governing the adoption of these tools are only studied recently and are not well understood (Huang *et al.*, 2022). Involuntary use of technologies increases anxiety and reduces technological trust which adversely affects the use of the technology and the overall perception of the institution executing the mandate (Cserdi and Kenesei, 2021).

Institutions are important for leading the development of technical and normative frameworks in key areas such as AI (e.g. Council of Europe, Organization for Economic Co-operation and Development). Already, there exist heated debates on the most viable way to move forward given the threats of surveillance, and market power misuse at many places and levels from local city government to regional lawmakers resulting in many initiatives, policies, and regulations being enacted (Gasser and Almeida, 2022). The pandemic has accelerated the adoption of technologies and highlighted the transformational power of data in governance. Restarting the economy would necessitate regulatory bodies to provide a transparent, and inclusive system for civilians. For example, a recent GovTech Summit (Skelton, 2020) on the deployment of government technology highlighted trust to be the single most important feature for the continued use of such technologies or if they are to be redeployed for future pandemics, especially in data-intensive systems such as the artefact in the study. In the United Kingdom (UK), the track-and-trace system was launched despite failing an obligatory mandate for data protection impact assessment resulting in a call to re-establish public confidence (Scroxton, 2020). It can be seen here the importance of users developing the trust that the institution will act more or less in one's and the public's interest, legitimately and ethically. The UK's Plan for Digital Regulation (2022) outlined technology as a key driver for growth along with the need for a supportive regulatory approach that stimulates innovations. Building on the UK's reputation for rule of law and technological breakthroughs, clear guides on the ethical use of technologies that protect citizens' fundamental rights and freedom while creating a digital economy that promotes a flourishing society are important to transform governance. Von Hanxleden (2022), presented an important "trilemma" related to information sovereignty. While it is clear that one's right to informational self-determination should not be compromised, decisions cannot be solely driven by potential privacy and risks. Much-needed aggregate knowledge should be contributed because losing other objectives in favor of one can lead to suboptimal results. Hence, to ensure the benefits of emerging technologies are harnessed, it is necessary to also consider the balance of power to minimize the negative effects and risks on society. Technology is driving the future, but the question is who is steering. In the end, it is about trust – trust in those who are in charge of handling our data responsibly.

Individual perspectives and trust in AI-tech

Privacy concerns between firms and consumers lead to consumers' reactions to the information collected (Krishen *et al.*, 2017). Firms have the responsibility to safeguard and maintain good data management practices. Responsible corporate privacy (CR) practices should support users' control over their personal data to allow them to decide how their data can be used (Bandara *et al.*, 2021). Any violation of such exchange could result in hostile emotions and affective states. Regrettably, COVID-19 and the nature of AI-tech coupled with big data analytics do not always afford users complete control over the collection and use of their data.

The mandated adoption entails collecting personal data, location tracking, and maybe the health vitals of users. At the heart of this is the question of whether users are agreeable, emotionally stable, and open (Junglas *et al.*, 2008) to AI-tech and whether they are empowered to protect their own data while engaging in AI-tech.

Empowerment is a reflection of control, awareness, self-determination, and self-efficacy (Bandara *et al.*, 2021). Being in control enables one to exercise influence over decisions that matter (Malhotra *et al.*, 2004) and is often related to physical and mental well-being, and conversely, a "subjective lack of control" leads to feelings of anxiety and depression (Wnuk *et al.*, 2020). There exists a dichotomy in generation privacy threat attitudes: some believe they have lost control over their personal information, while others feel that senior users do not need to worry as much as younger users. This is due to the belief that users lack control over their information (Frik *et al.*, 2019). Hence, privacy empowerment (PE) is related to "individuals' perception of the extent to which they can control distribution and use of their personally identifiable information" (Van Dyke *et al.*, 2007, p. 73).

Propensity to trust (PT) is a consistent tendency to trust which is neither trustee-specific nor situation-specific (McKnight *et al.*, 2011). According to Mayer *et al.* (1995), determinants of a trustee's trustworthiness are formed based on the trustor's beliefs in the ability, benevolence, and integrity of the trustee. Trust in a specific technology is influenced by a user's PT just as an individual has a PT to a person, the same person owns an innate PT in machines and vice versa (Merritt and Ilgen, 2008) across all situations. Users are willing to trust online vendors despite lacking information about them (Salam *et al.*, 2005) and technology-savvy users are more trusting in general (Leonard and Jones, 2021). Based on the above, this study hypothesized the following:

H1: Responsible Corporate Privacy (CR) has a positive effect on AI-tech Trust (AIT)

H2: Privacy Empowerment (PE) has a positive effect on AI-tech Trust (AIT)

H3. Propensity to Trust (PT) has a positive effect on AI-tech Trust (AIT)

Institutional perspectives and trust in AI-tech

Regulatory protection (RP) refers to the regulations of government and industry firms devised to govern consumer data usage (Lwin *et al.*, 2007) and is a critical factor in achieving healthy interaction between users and firms (Bandara *et al.*, 2021). Government plays a critical role in safeguarding the impact of AI-tech (Bano *et al.*, 2021; Duan *et al.*, 2019) mandated for use during the pandemic. Limited in knowledge, users have relied on laws and institutional safety mechanisms for protection. A regulatory policy may thus, be used to attenuate reactance responses and increase affordance. To mitigate reactance against policies, the use of autonomy-supportive elements to policy or persuasions that avoid threats could afford choice. We argue that regulations will prompt users to respond favorably with persuasion to adopt AI-tech.

The next factor, self-threat (ST) is influenced by vulnerability to disease, specifically negative affect, and emotional signs (Pérez-Fuentes *et al.*, 2020) and the measures implemented (e.g., social lockdowns, changes in travel behavior) (Montemurro, 2020). A user experiences fear due to the perceived ST of COVID-19 (Lima *et al.*, 2020) and the more austere the threat is perceived, the more adversely affected they will be. Additionally, users view themselves as vulnerable to threats either when they have trouble using and configuring a particular technology and/or if they have limited knowledge of how the technology works (Frik *et al.*, 2019). In this situation, common mitigation strategies that users will adopt when some aspect of self is exposed to threat include turning to others for support and affirmation or limiting the use of technology, or withdrawing altogether (Frik *et al.*, 2019). Accordingly, this study hypothesized that:

H4: Regulatory Protection (RP) has a positive effect on AI-tech Trust (AIT)

H5: Perceived Self-threat (ST) has a negative effect on AI-tech Trust (AIT)

Based on the hypotheses above, a research model is proposed to hypothesize the relationships between the selected antecedents as shown in Figure 1 below.

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Research Methodology

Data collection and sampling method

The study focused on Malaysians with experience in using AI-tech for travelling. Using a similar approach by Tan and Ooi (2018), close-ended questionnaires were distributed in Klang Valley between August to September 2020. Klang Valley was chosen for its cultural, technological, and economic representativeness in Malaysia and is deemed sufficient to generalize the different populations in Malaysia (Shafiq *et al.*, 2019). Purposive and system probability sampling was adopted as part of the research design whereby every fifth of the respondents was intercepted. The respondents were briefed on the purpose of the study and their willingness to participate. One filtering question on whether the participants have experience using AI-tech for travelling was included in determining the suitability of the respondents. Only respondents that have agreed were invited to fill up the remaining questionnaire. The questionnaires were collected immediately after completion. Lee *et al.* (2019, p. 601) concluded that “despite considerable effort and time, this method ensured a high response rate, with participants paying serious attention to their responses to the survey items. It also allowed the respondents to get clarification on any unclear survey questions/items”. Before data collection, the content validity of the survey instrument was assessed by 5 academic researchers specialized in the tourism industry for content validity. A few adjustments were made to the wording, content, sequence, layout, and format of the questions. The study then conducted a pilot test to check the scale’s validity and reliability. Subsequently, 250 questionnaires were distributed to which only 209 responses were usable in the analysis after removing missing values (more than 15 percent) and straight-lining responses. Mean value replacement was adopted if there are less than 5 percent of missing values per indicator.

Measurement instrument

The measurement items were adapted from past literature to accommodate the context of the study and scored on a seven-point Likert-type scale (1 = strongly disagree and 7 = strongly agree). All constructs were adapted from past studies to suit the current context: ST from Carpenter *et al.* (2019) and Le *et al.* (2022); PE from Bandara *et al.* (2021), and Pizzi and Scarpi (2020); CR and RP from Bandara *et al.* (2021); PT from Che *et al.* (2017), Gu and Wei (2021), Nordheim *et al.* (2019); and AIT from Pizzi and Scarpi (2020), and Pillai and Sivathanu (2020). The first section of the questionnaire identified the social-demographic characteristics of the sample. The second section collected data on respondents' views on the proposed constructs of interest.

Data Analysis

On gender, females constituted the major percentage at 58.37% whereas 41.63% were males. In terms of age, 42.59% of the sample fell below 30 years old. Furthermore, 51.67% of the samples are single. On the experience of using AI-based tourism products, 52.63% have less than 3 years of experience. On income, 11.48% fell below RM1,001 (approximately USD224), followed by RM1,001 to RM3,000 (approximately USD224 to USD672; 37.32%), RM3,001 to RM5,000 (approximately USD672 to USD1,120; 27.75%), RM5,001 to RM7,000 (approximately USD1,120 to USD1,566; 12.92%), RM7,001 to RM9,000 (approximately USD1,566 to USD2,016; 4.78%) and above RM9,001 (approximately USD2,016; 5.74%). Finally, in terms of education, 43.06% have a bachelor's degree or professional qualification. The demographic profile is shown in Table 1.

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Statistical analysis

Partial Least Squares (PLS) implemented in SmartPLS (version 3.2.9) was adopted to test the conceptual model. In contrast to covariance-based (CB) structural equation modelling (CB-SEM), PLS is appropriate as the method focuses on exploratory research and theory building (Zhu *et al.*, 2019). The study complies with the PLS purpose of prediction by integrating AIT, CR, PE, PT, RP, and ST in a new context of tourism. PLS-SEM is also ideal for data that does not meet the normality requirements (Tan and Ooi, 2018). The result indicates that the multivariate distribution of the data is not normal as Mardia's multivariate skewness (β = 11.755, $p < 0.001$) and Mardia's multivariate kurtosis (β = 81.022) have p-value < 0.001 respectively. G*Power (version 3.1.9.2) was used to determine the minimum sample size. Based on the power level of 0.80, 5 predictors, alpha value of 0.05, and an effect size of 0.15, as the level of the standard parameters, the required sample size is 92. Thus, our sample size of 209 is more than sufficient for employing the PLS technique.

Common Method Bias

To check for common method variance (CMV), a statistical approach was adopted in this study. First, we conducted Harmon's single factor analysis and as the first construct caused 46.023% of the total variance and is below the threshold value of 50 percent, this means that CMV is not present in this study (Podsakoff *et al.*, 2003). Further, we tested the CMV using the approach suggested by Liang *et al*. (2007). As shown in Table 2, all substantive factor loading (Ra) is significant at $p < 0.001$ with the average of Ra (0.825) greater than Rb (0.001). Additionally, as most of the items in method factor loading (Rb) are insignificant except AIT1 and PE1, this suggests that CMV is not a major concern in this study (Lew *et al.*, 2020). Several procedural remedies such as guaranteeing the anonymity of respondents and using simple and concise sentences were deployed during the development and administration of questionnaires (Hew *et al.*, 2020).

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Assessing the Outer Measurement Model

To check on the outer measurement model, a path weighting scheme estimation and Mode A was used. In measuring reliability, composite reliability (CRE) was used, and Table 3 shows that CRs were above the minimum level of 0.70 (Ooi and Tan, 2016). Unlike CR which measures sum scores, Dijkstra-Henseler's rho (rhoA) was also adopted to check for reliability. All the exogenous and endogenous constructs used in this study were above the recommended 0.70, indicating the support of satisfactory reliability (Chowdhury *et al.*, 2019). Further factor loading (FL) and average variance extracted (AVE) were applied to examine convergent validity. Table 3 indicates that all individual FLs are significant at $p < 0.001$ level and were greater than the threshold of 0.7 (Lee *et al.*, 2019) except ST4. As the AVE for ST is above 50 percent, ST4 can be accepted (Tan and Ooi, 2018). Additionally, AVE for each construct falls within the range of 0.583 to 0.798 and exceeds 0.5. Both criteria have proved that the study has good convergent validity (Loh *et al.*, 2022). The discriminant validity (DV) was performed using the Hetero-Trait-Mono-Trait (HTMT) ratio of correlations in Table 4 DV does not pose any problem because all HTMT values are below the conservative value of 0.85 (Chowdhury *et al.*, 2019). Additionally, an HTMT inference test was employed to check whether the values were significantly different from one. Using 95% confidence intervals, the upper and lower bounds revealed that none of the confidence intervals significantly differ from one indicating good DV (Tan and Ooi, 2018).

<< TABLE 3 HERE >>

<< TABLE 4 HERE >>

Inspecting the Inner Structural Model

This study adopted Standardized Root Mean Square Residual (SRMR) to check for model fit. SRMR values for both the saturated and estimated model is below the 0.08 threshold, which indicates that the model has a good fit with the empirical data (Hair *et al.*, 2017). The degree of multicollinearity among all constructs was assessed by the variance inflation factor (VIF).

The VIF values are between 1.362 to 3.432 and are below 10.00 which means that the result did not pose a multicollinearity problem (Wong *et al.*, 2020). To assess the hypothesized relationships, the p-value for each path coefficient is calculated using a bias-corrected and accelerated (BCa) bootstrap procedure with 5000 subsamples at a two-tailed 0.05 significance level. As shown in Figure 2 and Table 5, all proposed path coefficients are supported except hypotheses H1 and H2. Specifically, no direct relationship could be established between CR and AIT ($\beta = 0.013$, $p > 0.05$) and as well as PE and AIT ($\beta = 0.123$, $p > 0.05$). The bias-corrected confidence intervals for 2.5 and 97.5 percent further confirms the non-significant relationship between CR and AIT (2.5 percent = -0.141 and 97.5 percent = 0.181) and as well as PE and AIT (2.5 percent = -0.045 and 97.5 percent = 0.284). The quality of the model was evaluated by the variance explained or R^2 is 63.6% for BI which according to Seethamraju *et al.* (2018) is moderate.

<< FIGURE 2 HERE >>

<< TABLE 5 HERE >>

The Predictive Relevance and Effect Size

The f^2 effect size shows the impact of predictor constructs on AIT. The effect size of the exogenous constructs such as CR, PE, PT, RP, and ST are 0.000, 0.017, 0.296, 0.033, and 0.165 respectively. Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects while values below 0.02 have no effect (Tan and Ooi, 2018). Thus, all the predictor constructs have small effects while PT has a medium effect, and CR and PE have no effect. The blindfolding method with an omission distance of 7 was used as a criterion to check on Q^2. The value of Q^2 under column Q^2 (1-SSE/SSO) is 0.461 and thus is greater than zero. This implies that the model exhibits predictive relevance.

Discussion and Implications

Many studies have been conducted on the adoption of technologies during crises both from enterprise (Gaur *et al.*, 2021; Modgil *et al.*, 2022) and consumer (Duan and Zhu, 2020; Duan and Deng, 2021; 2022) perspectives. The depth of such engagements at an individual, employee, or business level is significant. According to Modgil *et al.* (2022), the literature indicated a huge market scope for digital innovations that address the public crisis which lies in artificial intelligence among other technology applications. Although their study focused on digital entrepreneurship opportunities, nevertheless it highlighted the pervasiveness of AI's role as an inseparable part of individuals' lives and in meeting societal needs. This is also supported by some recent literature (Gaur *et al.*, 2021; Gunasekeran *et al.*, 2021).

In this study, we argue that the adoption and consequent benefits of AI-tech are questionable. In the case of organizational adoption success, employee adoption is a necessary step (Venkatesh, 2021). Along this line of reasoning, we opine that consumer adoption is necessary for business/enterprise adoption and its consequent success. There are many aspects where consumer adoption could be hindered despite being mandated; some are integral to the characteristics of AI applications. For example, it is crucial to scale up the adoption rate of innovations with the right response and intervention strategies during the onset of a crisis. The Diffusion of Innovation Theory (Huang *et al.*, 2022; Rogers, 1995) outlined the gap between implementation and adoption due to the varying pace of acceptance and adoption. Noting this gap and considering the choice of mandated adoption we can infer this as a measure to narrow the gap. However, this revealed another possible reaction which is the focus of this work. The psychological reactance (Brehm, 1989) of users against the affordances of an innovation. Both of these have been extensively studied in the context of technology adoption as well as in the travel and tourism sectors (e.g. Feng *et al.*, 2019; Ghazali *et al.*, 2018; Gössling, 2021; Lei *et al.*, 2019).

The use of AI-tech introduces ethical, legal, and governance challenges (Huang *et al.*, 2022; Mikalef *et al.*, 2022a; Ryan, 2020). Critically, the mass adoption of AI-tech is powered by the generation and consumption of a huge amount of private data and actual decision-making. The user is left with little to no control over his or her data. Challenges such as knowledge deficits, fears of data mishandling, and mistrust in governments have all led to hesitancy in adoption (Chen *et al.*, 2021; Duan and Deng, 2022; Ong and Loo, 2022; Zimmermann *et al.*, 2021). Furthermore, we opine that the "right to be forgotten" in this case is locality dependent as users must part with their private data without explicit consent. For instance, under the GDPR, independent supervisory authorities are empowered to ensure the rights of data subjects be respected (including the right to be forgotten/erasure) whereas, in the United States, businesses that collect information on California residents need only inform them of the intended uses (Bradford *et al.*, 2020). This means entities other than health care agencies may freely collect data without the need to seek explicit consent. Hence, the use of AI-tech is certainly not without its perils. It raises many questions on users and governance in the form of regulations to establish trust and work within the confines of legal systems. According to Mikalef *et al.*

(2022a), the use of AI-tech should be ethical, transparent, and accountable. Further, this must be consistent with user expectations, and institutional values that assimilate with regulations and societal norms. Hence, this work adopted an individual and institutional view to understanding the formation of trust for the use of AI-tech. Thus, we maintain that trust is the central facilitator for user adoption as was also studied by many scholars (e.g. Gillath *et al.,* 2021; Glikson and Woolley, 2020; Lankton *et al.,* 2015; Ong and Loo, 2022; Robinson, 2020; Sullivan *et al.,* 2020)

In our hypotheses, all 5 key factors were expected to be positively associated with the development of trust in AI-tech. There are many characteristics of AI-tech that are correlated to the antecedents selected. The use of AI-tech as discussed earlier affects users' notion of PE as information is provided to the government-mandated app. There is no opt-out choice, and the person's travel history is stored and kept by another authority. Although not in the scope of this paper, there were many reports of data leaks, profiling, and breaches even of government agencies that constitute ST. PT is a generic trait that can be applied across many technologies; however, we believe that the inclusion of propensity to trust makes an interesting trait when considering the conflicting aspects of affordance and reactance. In the institutional aspect, RP and CR were included for the distinct reason that the use of AI-tech is government-mandated, it is new to both regulatory bodies and organizations in the hospitality field. As discussed in the introduction, past studies in tourism have considered such works for policy planning and possible insights. Therefore, this study included the two antecedents in the conceptual model.

The results indicate that ST, PT, and RP are significant for AIT. Both CR and PE to AIT are non-significant. In this study, the government-mandated use of a tracking app requires all travelers (local and international) to download the application and register using their national identification. First, this mandated adoption of AI-tech violates the freedom-of-choice beliefs of users and will result in opposing behavior. They can neither reject nor fabricate information while using AI-tech leading to the perceived loss of control. Research has yet to examine whether a lack of personal control would be related to the acceptance of measures that also pose a threat to privacy (Wnuk *et al*., 2020).

ST and PT in relation to AIT are both supported. In explaining ST to AIT, this study contends that the use of AI-tech when perceived as a self-threat, leads to anxiety, and trust in AIT is affected. This is further supported by the slow uptake of the mandated app (Bano *et al.,* 2021). PT is innate. Naturally trusting users will accordingly trust AI-tech or are motivated to acquire further information to afford AIT. Next, RP is supported. When users perceive the regulations in place are robust and can afford protection, they are more likely to place trust in AI-tech and not develop a negative perception.

The results of this study revealed that the relationship between PE and AIT was weak. This situation can be explained as a trade-off for freedom to travel users who would have made a rational choice in information disclosure despite having privacy concerns. Further, many places that allow the use of a generic scanner to register or logbooks to record information of visitors provide an opportunity for data fabrication and in that sense can be viewed as an act of freedom restoration in accordance with the reactance theory. CR is a persuasion meant to reach the desired goal. This finding can be construed as an attempt at regaining control on the part of users and a flaw in enhancing the persuasion message. Technological solutions during COVID-19 were repurposed quickly for use and the lack of trialability of such solutions is debatable. This is in line with an earlier discussion on the erosion of trust due to incompetent technological solutions. In Germany, citizens were more resistant to using the app despite "sincere efforts" to increase trust via transparency of their Corona-Warn-App development (Bano *et al.*, 2021, p. 10). Another plausible explanation is the phenomenon of security fatigue which refers to the desensitization experienced by users who become weary and disillusioned with security (Turel *et al.*, 2019), privacy helplessness that explains users' belief of uncontrollable and inevitable privacy risks (Cho, 2022; Zhu *et al.*, 2021) and privacy fatigue where users allow the unconditional collection and processing of personal data despite privacy doubts due to a sense of futility or loss of control over personal information (Zhu *et al.*, 2021).

Implications for Research

In this work, we posit that every innovation, specifically technological innovation is a tool created for the accomplishment of a particular objective. Through the lens of individual and institutional perspectives, this study undertakes to investigate the formation of trust in the technology by considering the affordances against the reactance effects. Past studies have mainly studied affordances or reactance separately while in our work, we adopted a holistic approach to this. There are a few reasons which have guided us in the design of this research.

Generally, people will consent to health systems' use of their data for tracking, but this is not the optimal basis for public authorities (Bradford *et al.*, 2020). What is given due to power or potential power to compel compliance cannot be considered free will. Ideally, this would suggest that the mandated use of technologies should also include an option to revoke consent at any time. However, if such an option were to be provided, this would compromise the original intent of mandating such an adoption which surely defeats the vital purposes of protecting the public and monitoring the spread of a crisis. That said, the advent of technology such as AI-tech and big data requires additional justifications particularly in terms of responsible use, explainable use (Mikalef *et al.*, 2022a), and just regulatory frameworks (Mikalef *et al.*, 2022b) and the need for principles that guide both private and public organizations (Jobin *et al.*, 2019). Promoting voluntary use is arguable as to whether it will be effective in preserving its mission and original intent.

While the affordances of AI-tech are apparent, we posit that both institutional and individual roles warrant further studies. For instance, human biases could be as severe and may lead to grave mistakes as they may opt to trust their judgements or colleagues' judgements over that of the application (Venkatesh, 2021). And for some, concerns about privacy and data security deter adoption (Duan and Deng, 2022; Huang *et al.*, 2022). In India for example, the Arogya Setu contact tracing application was initially adopted voluntarily but subsequently became a mandated condition for returning to work notwithstanding its privacy concerns (India Today Tech, 2020). On the flip side, the implementation successes of Taiwan, South Korea, and Singapore on the other hand, can be attributed to supporting existing laws on privacy and data governance (Back *et al.*, 2021).

There are perhaps as many discussions on the inherent biases of AI models (Liang *et al.*, 2021; Marjanovic *et al.*, 2022; Mikalef *et al.*, 2022a) as there are on the merits of smart technologies assisting users in daily tasks (Cao *et al.*, 2021; Duan *et al.*, 2019; Dwivedi *et al.*, 2021a; Seeber *et al.*, 2020). While we admit that there are many factors leading to trust, we agree with Mikalef *et al.* (2022a) that empirical studies on organizational, business units, and individual levels are scarce, and iterate that the dimensions adopted in this study are complementary and crucial to providing a holistic understanding on users and institutional efforts. There are limitations in our work, which must be acknowledged. We hope that future research can be undertaken to complement the findings of our work and to add further insights into understanding the adoption and resistance of technologies.

According to Dwivedi *et al.* (2021a), AI-tech can potentially impact human lives and society at large but its potential roadmap is unclear with inherent risks that deprive society of implementation. Yet, it remains unclear if there exists a better framework that could enhance trust and understanding of AI-tech in travel and tourism (Park, 2020; Tussyadiah *et al.*, 2020; Williams and Baláž, 2020). Despite that, a clear indication from this work is that AI-tech should be designed to positively impact social response. Dwivedi *et al.* (2021b) underscored the source, receiver, message, medium, and contexts as elements that affect persuasion and influence of communication. There is a pressing need to answer who is accountable when things go wrong (Dwivedi *et al.*, 2021a; Liang *et al.*, 2021) to comprehend the implications of AI-tech for key stakeholders. From an institutional perspective, Liang *et al*. (2021) call for IS scholars to promote AI suitability or an "affordance directed at designing AI" (p. 8) systems that are compliant with laws, regulations, or policies. This is critical to addressing accountability and privacy-related issues. Xu and Wu (2020) showed the possibility of corporate communication during crises may result in considerable negativity if not well managed. Under extenuating circumstances, persuasive communication is crucial to effectively manage and navigate the challenges of a crisis thereby implying that further possible mediators may be considered. Future work could examine the role of information quality against decision evaluations. Echoing Dwivedi *et al*. (2021a), policies of long-term strategies may no longer suit AI-tech's pace of change. Further, the sanctioning of AI-tech within industry and government depends on market perspectives. There is a need to revisit the implications of AI-tech and regulatory options both in a societal context and globally to address the knowledge gap. Ultimately, although technology is meant to bring greater utility to users, it remains unknown who ultimately gains the advantage and who pays the price (Liang *et al*., 2021).

Implications for practice

Mandates by institutions and tourists' evaluation of trust are both sides of the equation that needs to be balanced to restart tourism. According to Grover *et al.* (2022), the success of AI-tech depends on the synergetic relationship between users and the AI-tech whereby the key implementation decisions revolve around data source, algorithm, and training and deployment. Therefore, addressing the initial perception of confrontation with AI-tech in travel and tourism is important to manage the magnitude of reactance. User expectations and preferences for technology-based engagements can assist firms to promote customer differentiation and afford greater value for them (Dwivedi *et al.*, 2021b). For instance, announcing in advance crucial information to users helps to foster passive acceptance of AI-tech (Heidenreich and Talke, 2020). The key lies in the persuasion that delivers the message: AI-tech is not a hassle but a voluntary willing step necessary to add value to freedom.

Next, providing different coping strategies based on needs and purposes can alleviate reasons for resisting mandated adoption. Tourists can be trained on security mechanisms and informed of security issues related to their data (Pillai *et al.*, 2020). Systems must be in place to inform tourists regarding fraud and unauthorized usage. Tourists who receive responsive and continuous support post-adoption will experience heightened confidence and trust. Furthermore, prioritizing security and privacy communications increases user trust (Casaló *et al.*, 2007). Firms need to enhance user perceptions of their protection by regulatory bodies and show that they are responsible for safeguarding user welfare (Lwin *et al.*, 2007). Firms can work proactively with enforcement bodies to achieve mutually beneficial conditions and communication with users. Consumer satisfaction typically measures the discrepancy between customer expectation and perceived performance. When customer expectations of the safeguards afforded by AI-tech usage and the environment matches perceived performance, it can be inferred that trust formation will occur. This concurs with the initial trust-building model that trust is an interplay of both institutional and disposition to trust. And further trust is a function of an interplay of one's attitudes and beliefs.

Conclusion

This study draws on the affordance and reactance theories as the basis to test a conceptual model of trust in AI-tech in travel and tourism. Specifically, this study examines how perceptions of affordance or reactance provoke resistance or persuasion to the use of AI-tech owing to perceived ST, PE, RP, CR, and PT in developing trust. Set in the context of mandated use, this work also offers many research and practical implications for institutions, policymakers, and managers to intervene and enhance user satisfaction in the persuasion of AI-tech use. Technological solutions are of little use if the bigger picture and the complex interplay between user and institutional factors are not understood. Hence, future studies can enhance the generalization of the findings via a comparison between countries of key players in AI-tech and developing countries. Second, a longitudinal study can be designed to consider a continuance perspective with a larger sample size. Third, the model used ST, PE, RP, CR, and PT and this has limited representation, therefore future studies may deploy other factors that may affect AIT. Finally, trust is multi-facet and at what stage do negative aspects of mandated usage contexts erode or build trust can be further studied.

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Figure 1. Research Model

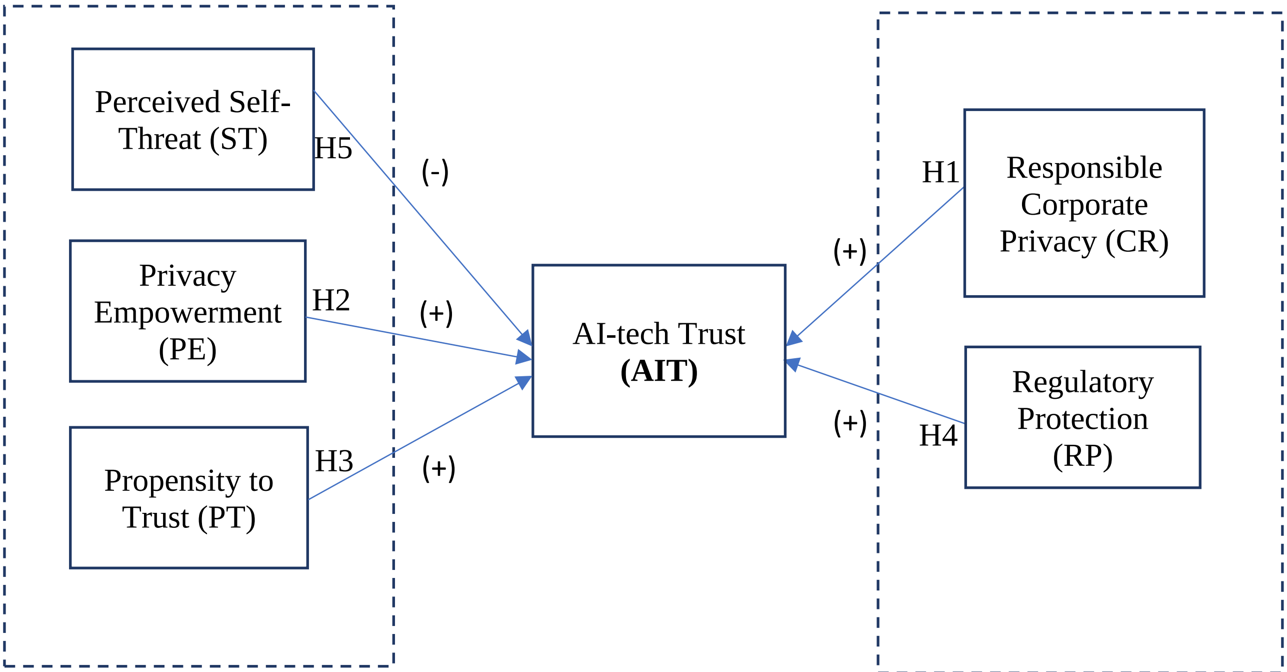
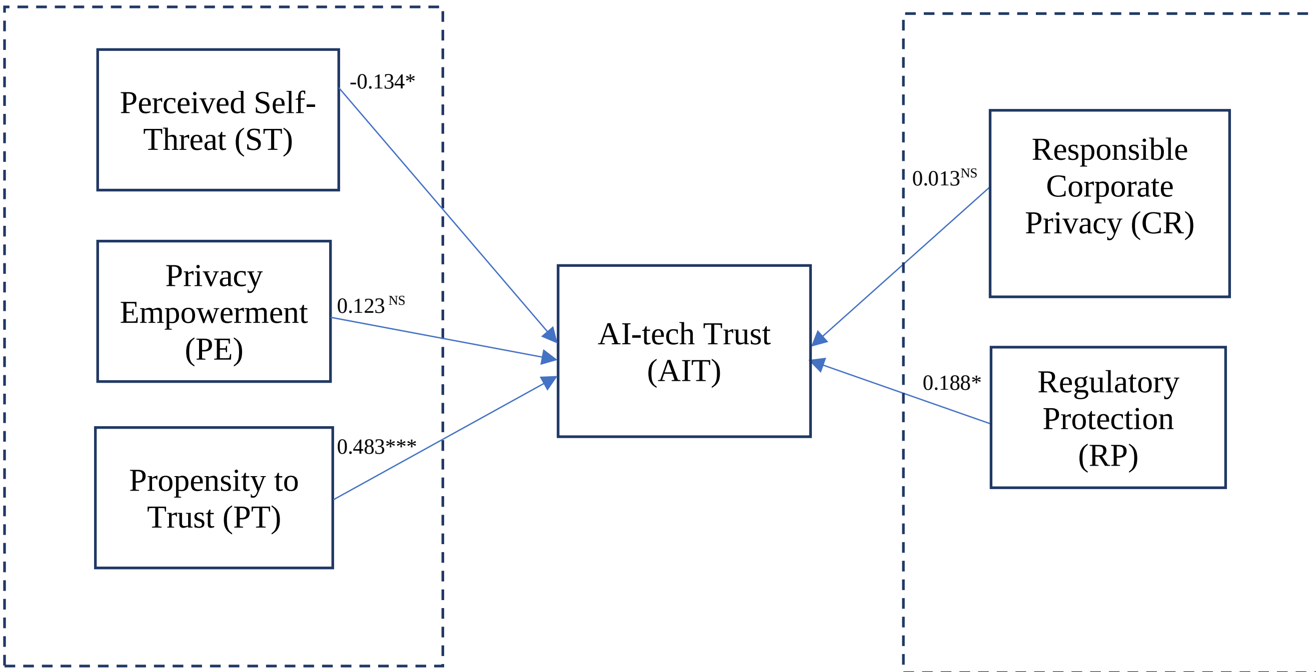


Figure 2: Result of Hypotheses Testing



Notes:
**p* <0.05; ****p* <0.001; NSnot significant

Table 1: Descriptive Characteristics of the Participants

Demographic Characteristics		Count	Percentage (%)
Gender	Male	87	41.63
	Female	122	58.37
Age	Below 15 Years	1	0.48
	15 - 19 Years	2	0.96
	20 - 24 Years	47	22.49
	25- 29 Years	39	18.66
	30 – 34 Years	30	14.35
	35 - 39 Years	40	19.14
	40 - 44 Years	27	12.92
	45 - 49 Years	15	7.18
	Above 50 Years	8	3.83
Marital Status	Single	108	51.67
	Married	101	48.33
Experience of using AI based tourism products	Below 3 years	110	52.63
	3 - 5 Years	48	22.97
	Above 5 Years	51	24.40
Monthly income	Less than RM1,001	24	11.48
	RM1,001 to RM3,000	78	37.32
	RM3,001 to RM5,000	58	27.75
	RM5,001 to RM7,000	27	12.92
	RM7,001 to RM9,000	10	4.78
	RM9,001 and above	12	5.74
Highest level of education	No College Degree	23	11.00
	Diploma / advance diploma	65	31.10
	Bachelor's degree / professional qualification	90	43.06
	Master / PhD degree	31	14.83

Table 2: CMB Analysis

Latent Construct	Indicators	Substantive factor loading (Ra)	Ra^2	Method factor loading (Rb)	Rb^2
AIT	AIT1	0.997^{***}	0.994	-0.151^{*}	0.023
	AIT2	0.808^{***}	0.653	0.007^{NS}	0.000
	AIT3	0.784^{***}	0.615	0.122^{NS}	0.015
	AIT4	0.869^{***}	0.755	0.019^{NS}	0.000
CR	CR1	0.747^{***}	0.558	0.030^{NS}	0.001
	CR2	0.789^{***}	0.623	-0.010^{NS}	0.000
	CR3	0.839^{***}	0.704	0.037^{NS}	0.001
	CR4	0.902^{***}	0.814	-0.058^{NS}	0.003
	CR5	0.892^{***}	0.796	0.001^{NS}	0.000
PE	PE1	0.992^{***}	0.984	-0.169^{*}	0.029
	PE2	0.878^{***}	0.771	-0.084^{NS}	0.007
	PE3	0.691^{***}	0.477	0.083^{NS}	0.007
	PE4	0.860^{***}	0.740	-0.055^{NS}	0.003
	PE5	0.540^{***}	0.292	0.239^{NS}	0.057
	PE6	0.719^{***}	0.517	0.013^{NS}	0.000
PT	PT1	0.517^{***}	0.267	0.249^{NS}	0.062
	PT2	0.698^{***}	0.487	0.058^{NS}	0.003
	PT3	0.926^{***}	0.857	-0.110^{NS}	0.012
	PT4	0.944^{***}	0.891	-0.149^{NS}	0.022
	PT5	0.830^{***}	0.689	0.063^{NS}	0.004
	PT6	0.942^{***}	0.887	-0.085^{NS}	0.007
RP	RP1	0.890^{***}	0.792	0.004^{NS}	0.000
	RP2	0.865^{***}	0.748	0.046^{NS}	0.002
	RP3	0.960^{***}	0.922	-0.072^{NS}	0.005
	RP4	0.941^{***}	0.885	-0.073^{NS}	0.005
	RP5	0.811^{***}	0.658	0.094^{NS}	0.009
ST	ST1	0.884^{***}	0.781	0.105^{NS}	0.011
	ST2	0.792^{***}	0.627	0.022^{NS}	0.000
	ST3	0.780^{***}	0.608	0.044^{NS}	0.002
	ST4	0.650^{***}	0.423	-0.060^{NS}	0.004
	ST5	0.709^{***}	0.503	-0.117^{NS}	0.014
Average		**0.825**	**0.693**	**0.001**	**0.009**

Notes:
***p<0.001; *p< 0.05; ^{NS}not significant

Table 3: Loadings, Composite Reliability, Dijkstra Henseler and Average Variance Extracted

Constructs	Items	Loadings (p-levels)	Composite Reliability (CRE)	Dijkstra Henseler's (rho_A)	Average Variance Extracted (AVE)
AIT	AIT1	0.874 ($p < 0.001$)	0.922	0.891	0.747
	AIT2	0.813 ($p < 0.001$)			
	AIT3	0.884 ($p < 0.001$)			
	AIT4	0.885 ($p < 0.001$)			
CR	CR1	0.785 ($p < 0.001$)	0.920	0.895	0.698
	CR2	0.776 ($p < 0.001$)			
	CR3	0.875 ($p < 0.001$)			
	CR4	0.845 ($p < 0.001$)			
	CR5	0.890 ($p < 0.001$)			
PE	PE1	0.844 ($p < 0.001$)	0.905	0.876	0.616
	PE2	0.798 ($p < 0.001$)			
	PE3	0.770 ($p < 0.001$)			
	PE4	0.815 ($p < 0.001$)			
	PE5	0.751 ($p < 0.001$)			
	PE6	0.724 ($p < 0.001$)			
PT	PT1	0.749 ($p < 0.001$)	0.922	0.900	0.664
	PT2	0.744 ($p < 0.001$)			
	PT3	0.825 ($p < 0.001$)			
	PT4	0.810 ($p < 0.001$)			
	PT5	0.884 ($p < 0.001$)			
	PT6	0.867 ($p < 0.001$)			
RP	RP1	0.896 ($p < 0.001$)	0.952	0.939	0.798
	RP2	0.904 ($p < 0.001$)			
	RP3	0.899 ($p < 0.001$)			
	RP4	0.874 ($p < 0.001$)			
	RP5	0.893 ($p < 0.001$)			
ST	ST1	0.816 ($p < 0.001$)	0.876	0.828	0.583
	ST2	0.776 ($p < 0.001$)			
	ST3	0.753 ($p < 0.001$)			
	ST4	0.685 ($p < 0.001$)			
	ST5	0.790 ($p < 0.001$)			

Table 4: Hetero-Trait-Mono-Trait Assessment

Latent Construct	AIT	CR	PE	PT	RP	ST
AIT						

CR	0.708 [0.571, 0.826]					
PE	0.675 [0.553, 0.785]	0.838 [0.746, 0.920]				
PT	0.839 [0.764, 0.905]	0.733 [0.570, 0.864]	0.639 [0.50, 0.771]			
RP	0.707 [0.584, 0.812]	0.840 [0.765, 0.902]	0.769 [0.663, 0.852]	0.707 [0.565, 0.829]		
ST	0.597 [0.453, 0.763]	0.575 [0.387, 0.747]	0.517 [0.328, 0.710]	0.603 [0.466, 0.732]	0.413 [0.240, 0.586]	

Notes: The values in the brackets represent the lower and the upper bounds of the 95% confidence interval

Table 5: Outcome of the Structural Model Examination

Hypotheses	PLS Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Bias Corrected Confidence Interval		Supported?
H1	CR -> AIT[NS]	0.013	0.022	0.084	0.151	0.880	-0.141	0.181	No
H2	PE -> AIT[NS]	0.123	0.124	0.084	1.453	0.146	-0.045	0.284	No
H3	PT -> AIT***	0.483	0.480	0.082	5.898	0.000	0.320	0.637	Yes
H4	RP -> AIT*	0.188	0.184	0.087	2.164	0.03	0.017	0.356	Yes
H5	ST -> AIT*	-0.134	-0.133	0.066	2.025	0.043	-0.263	-0.005	Yes

Notes:
*$p < 0.05$ level; ***$p < 0.001$ level; [NS]not significant