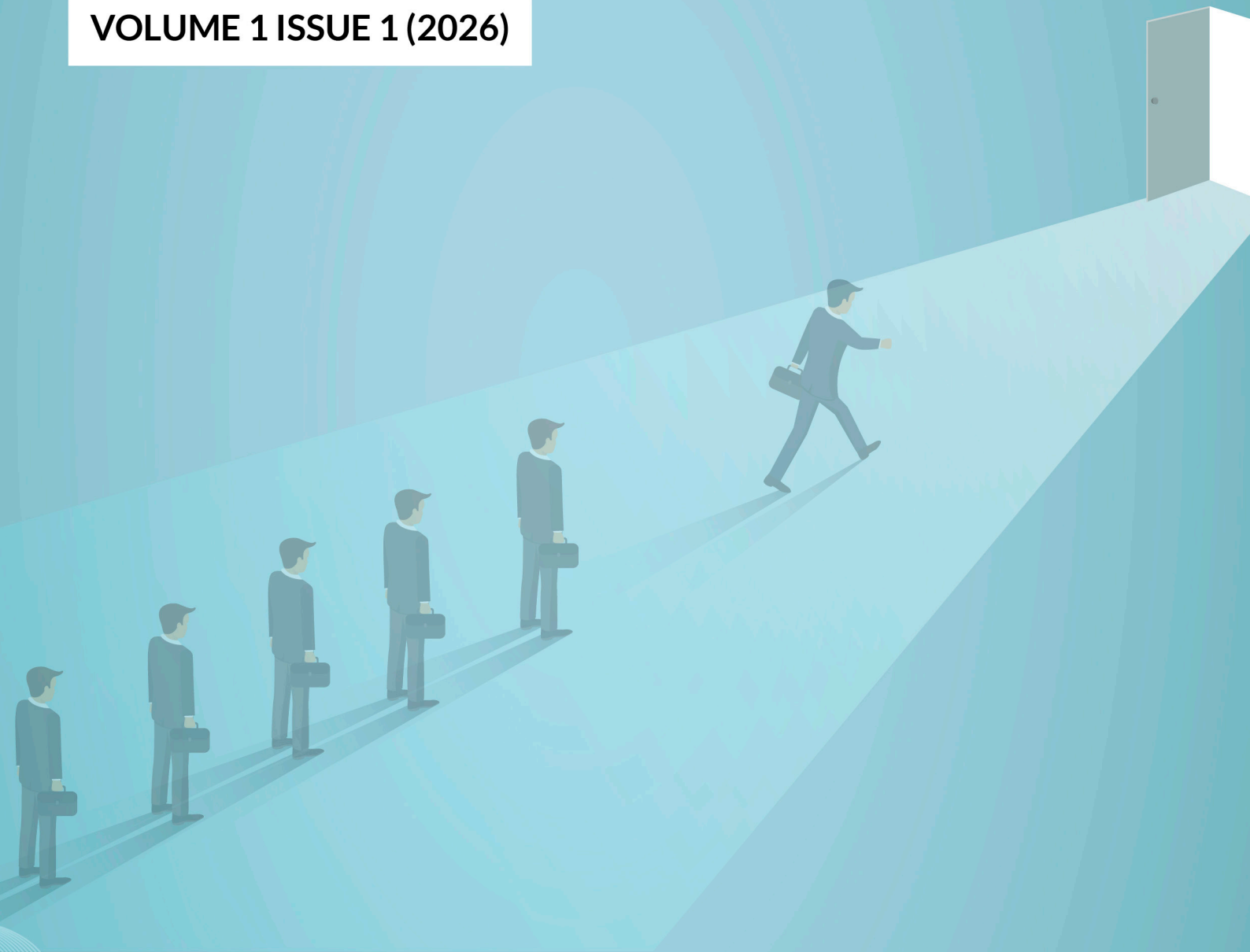
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# Artificial Intelligence Based Travel Recommendations and Tourist Decision Making: The Mediating Role of Trust

Md. Asadulla Al Galib[1*]

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## ABSTRACT

Travel suggestions which are artificial intelligence based give the tourist information and an alternative of suggestions as they are planning on their travels. The level of their participation in decision making is based on the perceived recommendation performance and trust in the recommending system. This research paper looks at the correlation between the recommendation quality, personalization, trust and tourist decision making through a provided survey analysis of 560 qualified records. Twenty statements measured on a five-point agreement scale were used to measure four reflective constructs. The analytical workbook has reported partial least squares structural equation modelling and 5,000 bootstrap resamples. Trust had a positive association with the quality of the recommendation and personalization with standardized coefficients of 0.3548 and 0.3456, respectively. They were directly correlated to tourist decision making with a value of 0.2186 and 0.1953. The most direct relation was observed between trust and decision making that was 0.4312. The indirect relationships based on trust were positive in case of recommendation quality 0.1530 and personalization 0.1490. Confidence intervals not equal to zero supported all the seven hypotheses. The model accounted 34.07% of the trust variances and 47.88% of the decision-making variances. The findings show the existence of complementary partial mediation, and the importance of information quality and preference compatibility to facilitate decision support in part via trust. It can only be interpreted on the basis of provided analytical records since the provenance of fieldwork and independent outcomes of behaviour were not recorded.

## INTRODUCTION

Travel planning involves consideration of destinations, accommodation, transport, activities and the amount of money spent under the circumstances of incomplete information. These options are interrelated. A destination may be appealing but inappropriate due to a traveling time, money, accessibility, or the presence of proper services. The process could potentially be assisted by artificial intelligence-based recommendation systems which pick alternatives and sort the information, based on the requirements we stated (Xu *et al.*, 2021). The practical usefulness can be defined on the basis of whether the tourists find the recommendations useful to make their decisions. The current research paper explores such relationship with recommendation quality, personalization, and trust. The main thesis is that perceived technical performance and preference congruence play a role in decision support both in a direct connection and an indirect connection via trust.

The quality of recommendations relates to the perceived accuracy, relevance, completeness, consistency, and clarity of information. The features are especially significant in situations where the tourists would not be able to examine the travel services prior to committing themselves (Asaithambi *et al.*, 2023). Inappropriate information may undermine a well-approved itinerary. Information that is not complete can impede a comparison of the alternatives. Confused descriptions may add more work to the process of appraisal of recommendations. Quality is hence more than presentation of beautiful destinations. It deals with the question of whether a recommendation gives a sensible and reliable enough basis on which to make a judgment (Cheng, 2021). The research considers this perception as a specific construct since a system is capable of generating clear and detailed information that is not a proper reflection of the situation of a specific traveller.

Personalization involves the relationship between the recommendations and the needs of individual requirements. These needs involve destinations of choice, budgets, activities, timeframes, length of trip, and travel needs. Even a technically correct recommendation might still be in-appropriate when it is out of the budget or does not take into account time limits on travel. On the other hand, a very personalized suggestion may be unreliable in case the information which it is based on is inaccurate (Yu *et al.*, 2020). The analysis of quality and personalization in combination makes it possible to estimate the separate statistical contribution of each of them. Such a difference also aids in explaining a practical design issue. Recommendation systems need to deliver information which is reliable but on the other hand the recommended alternatives need to have a meaningful response to the preferences made by the user.

Trust is placed between decision support and system evaluations. When there is still doubt about the recommending system, tourists might evaluate information as important but undue to that fact they may

[1] Lecturer, Marketing, Rajshahi Cantonment Public School and College, Bangladesh
[*] Corresponding author's e-mail: mdgalibru97@gmail.com

not trust it. Recommendations could be more effective in terms of influencing in the comparison and selection of alternatives because of confidence in credibility, dependability, and integrity (Sánchez-Ancajima, 2023). Trust does not mean that verification will not be done. A traveller may consider a system to be helpful when he or she checks the prices, availability, or entry conditions elsewhere. The construct, which is analyzed here, is the confidence in the source of recommendation when planning. It does not gauge freedom of unreliability, impartiality of the system, or lack of worrying about the potential mistakes.

The research question is whether the quality of recommendation and personalization still have direct relationships with tourist decision making since trust is entered, and whether trust statistically mediates some of the relationships. A model that could be restricted to direct correspondence would cause the role of confidence to be poorly defined (Cepeda-Pacheco & Domingo, 2022). An example that all the influence might go through trust would ignore the immediacy of useful information and the appropriate substitute. The current structure allows the two options. Tourist decision making is operationalized as a perceived assistant in the process of destinations identification, comparison of alternatives, choice of services, informed choice and selection of appropriate choices (Fudholi *et al.*, 2021). It is thus reported decision support and not checked off purchasing behaviour or objective quality of completed trips.

The research involves seven hypotheses in a quantitative paradigm. There are five hypotheses that deal with direct paths between the four constructs. There are two hypotheses with regard to indirect routes via trust. The analysis has been based on provided questionnaire plan, a statistical workbook and conceptual and structural diagrams. The workbook has findings on 560 records, whereas the proposal was a target of 550 on recruitment. Counting of analytics remains constant in the manuscript. Since the used materials do not define the recruitment processes and provenance of the fieldwork, the evidence is explained as a written review of provided survey data. This test identifies the range of the empirical research findings without changing the numerical findings presented (Gu *et al.*, 2020).

The research adds to the specific description of the relationship between the perceived recommendation performance and the travel choices. It establishes quality of information in general and congruence to individual preference as a parallel explanatory way and assessment of the magnitude of each association (Solakis *et al.*, 2024). It also decouples the measurement quality and interpretation of behaviour. Good reliability and statistically supported paths can provide internal consistency in the provided analysis, but never causality independently, the representativeness of the population, and effective travel results. These differences advocate disciplined interpretation of findings and give a foundation on practical recommendations in regard to information verification, controls on personalization, and communication of recommendation limits.

## LITERATURE REVIEW

### Recommendation quality and trust

An artificial intelligence powered travel suggestion system/advice is information selection with an implied rating of appropriateness. The result of that production can present concrete proofs on the basis of which the tourists can base their trust in the system. Precise details of destination also help to create an impression that recommendations are based on reliable information (Tuo *et al.*, 2021). Relevant options show concern to the request. Adequate detail enables tourists to examine the rationale of a suggestion. Consistency levels lessen the uncertainty between the criteria given and alternatives on offer. The output is made available in the form of clarity to facilitate comparison. Combined, these characteristics provide a viable foundation of trust but the current instrument gauges perceived and not a quality that is established independently (Fararni *et al.*, 2021).

Constructs of quality and trust are conceptually distinct. Quality is a description of a judgment of the output of recommendation. The term trust relates to trust in the source of that output. A traveller can get a straightforward answer but be lost between the commercial motives or the reliability of an unknown service. A different traveller might rely on a platform they know although they might not get a full recommendation (Yan, 2022). These opportunities warrant individual measurement. The hypothesized correlation is that positive judgments of the quality of output correlate with increased trust in the recommending system. The cross-sectional design will allow taking a measurement of that association, but not determining whether the quality perceptions are also influenced by prior trust (Zhou *et al.*, 2021).

**H1:** states that AI recommendation quality has a positive association with tourists' trust in AI based travel recommendations.

### Personalization and trust

Evidence of personalization can be based on the fact that the system is aware of the situation of the traveller. In the case when a suggested activity does not violate the financial restrictions, provides preferred activities, and accommodates the available schedule, the result is easier to perceive as reactive and reliable (Aguirre Montero & López-Sánchez, 2021). This alignment can lessen the uncertainty on whether the system is solving the real planning problem. Even the factual content of a recommendation that does not take into account those requirements can seem generic. The anticipated association with trust thus relates to perceiving responsiveness (Yun & Luo, 2022). It is not based on the assumption that more personal information, automatically collected, will make people feel better, or that all personalization is good.

There are limits to the mechanism as well. Unexplained

personalization can be considered intrusive by the tourists, or they can wonder how preferences were guessed (Erbil & Wörndl, 2022). The use of personalization, which is wrongly based on assumptions, would undermine trust. Such possibilities are applicable to system design, although among the present model, no attention was paid to privacy concern and transparency. It deals with the perception of recommendations indicated to be associated with stated needs. By that meaning, the favourable fitment of preferences is anticipated to go along with a greater trust (Lee *et al.*, 2022). The requirement of consent, correction and user control of personalized services is not incompatible with this expectation in the practical implementation of the customization of services.

**H2:** There is a positive relationship between personalization and trust of tourists towards AI based travel recommendations.

**Recommendation quality and tourist decision making**

The quality of recommendations would be able to assist in making a decision without reliance on trust by making it easier to structure and compare travel data. Effective description of the destinations can assist tourists to know the appropriate alternative. Critical service details can highlight the differences between options (Fan & Zhang, 2022). The comparison to similar travel criteria can be aided by using the same presentation. These functions will still be of use when the traveller keeps on checking the source of recommendations (Qin *et al.*, 2022). The proposed direct relationship is thus about the useful contribution of usable information to the reported decision support, assuming the presence of the other constructs in the structural model.

The outcome does not determine the objectivity of the optimal nature of a recommended option. Travel choices reflect preferences which can be different among people and situations. It is possible that a system can encourage choice without the result of the best price or the best subsequent satisfaction (Gao *et al.*, 2022). The tool rather measures the perception of respondents that recommendations help in particular activities of planning. Such definition puts the construct of quality in line with the informational requirements of the outcome and also maintains the distinction between them. Quality measures the nature of the information (Zhou *et al.*, 2022). Decision support measures how helpful or useful was the help one received by using that information in travel choice.

**H3** states that AI recommendation quality has a positive direct association with tourist decision making.

**Personalization and tourist decision making**

Decision making can be promoted using personalization to reduce the number of choices to alternatives with respect to relevant requirements. A budget traveler will not need to incorporate unwarranted accommodation. A day out can involve activities that can be contained within a limited schedule (Arefieva *et al.*, 2023). Certain accessibility or family considerations can alter what can reasonably be taken into account in terms of services. Such conditions can be matched with recommendations to produce less needless comparison and allow travellers to make viable decisions. This direct route is related to the utility of preference congruency despite any deliberation of confidence of the source of the recommendation (Ranga *et al.*, 2023).

Another issue with personalization is that it may generate a set of choices which is a bit too narrow in the case when the system gets the preferences too narrowly. The current hypothesis fails to prove the fact that more filtering will always be good. It deals with the appraisal of the recommendations by respondents that would suit their preferences and needs (Mule & Mulik, 2022). The difference is consequential in the sense that perceived compliance might underpin decisions and the alternatives that are not explored are not involved in the recommendation process. An overall assessment of personalization would thus comprise an appraisal of perceived suitability and variety of viable options. The latter is directly reflected in the provided measurement instrument only (Ercan, 2020).

**H4** is that there is a positive one-to-one relationship between personalization and decision making in tourism.

**Trust and tourist decision making**

Trust may have a role of the availability of information becoming grounds of action. A recommendation can include pertinent information, but the information can hold little decision-value in cases where the traveller questions their validity (Hu *et al.*, 2023). The ability to trust the source can also enable the tourist to withhold more focus on comparison of options as opposed to doubting the system repeatedly. The suggested correlation is thus between trust and perceived decision assistance. It does not mean that independence needs to be substituted by determining checks, or confidence assures proper information.

Trust can also assist in assimilating numerous planning judgements. The suitability of the destination, the choice of the service and finalization of the itinerary involves the tourists relating the information in multiple decisions. Continuity in these stages can be obtained by a reliable source of recommendations (Rokhsaritalemi *et al.*, 2022). The provided data fails to distinguish early exploration, though, and final booking. The result is a synthesis of multiple perceived assistance into a single construct. The interpretation of the relationship is then at that expanded level. It determines whether respondents who report higher trust rates also report higher rates of assistance with the travel determination when the factors of quality of the recommendations and personalization are incorporated (Xu *et al.*, 2021).

**H5:** There is a positive relationship between trust in AI based travel recommendations and tourist decision making.

### The mediating role of trust

Mediation argument is an amalgamation of the relationships mentioned above. The quality of the recommendations can be one factor that leads to trust as when the information provided is correct, relevant, and understandable, it is an indication of reliability (Asaithambi *et al.*, 2023). Trust can then be related to increased readiness to utilize that information when planning the trip. Personalization can also enhance confidence by illustrating consideration of preferences, and thereafter, recommendations are more effective when it comes to assessing and adjudicating the decisions. Such indirect pathways do not entail discontinuation of the direct relationships (Cheng, 2021). Preference alignment, informational usefulness and confidence may work jointly in the same explanatory model.

Complementary partial mediation would be supported by a positive indirect association and positive direct association. This would imply that trust is statistically significant in explaining a portion of the relationship, but retains a direct component. Here, the term mediation is employed in this statistical sense (Gu *et al.*, 2020). An occasion of measurement is not sufficient to determine that recommendation evaluations were made before trust or that trust was made before decisions. There are other possible temporal sequences. The analysis thus checks the consistency of the covariance structure provided with the postulated indirect pathways instead of purportedly proving a causal psychological process.

H6 declares that trust has a positive mediating role between the quality of AI recommendations and tourist decision making. H7: Trust has a positive mediation effect between personalization and tourist decision making (Solakis *et al.*, 2024). The conceptual structure can be found in figure 1. The quality of recommendations and personalization both relate to the trust and decision making, whereas trust relates to decision making. The two indirect hypotheses take the respective paths with trust. There are four reflective constructs, five direct structural paths and two specific indirect relationships in the framework.

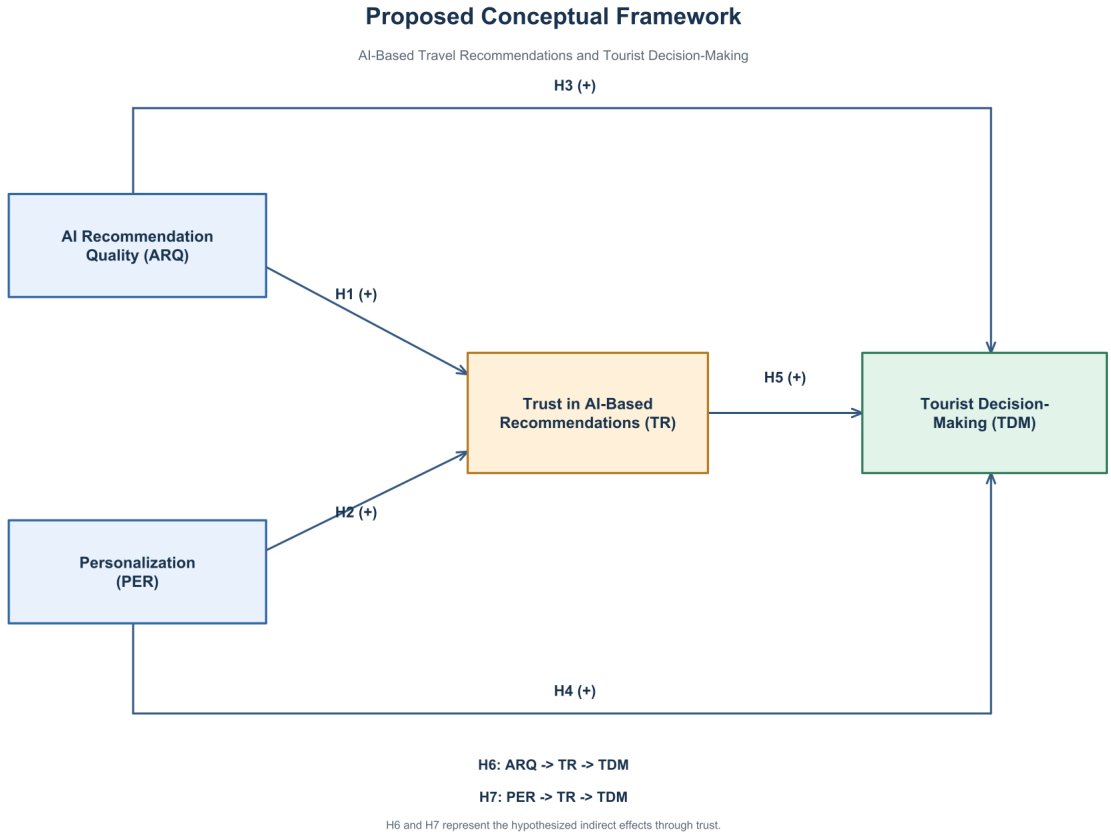



**Figure 1:** Conceptual framework and hypothesized relationships

## MATERIALS AND METHODS

### Research design and analytical materials

The experiment employs quantitative and cross-sectional study design in investigating the relationship between perceived recommendation quality, personalization, trust and tourist decision making. The materials at disposal include a proposed structured questionnaire, a completed statistical workbook and two model diagrams. The present manuscript reports the supplied analytical results. The workbook includes sample summaries, demographics frequencies, descriptive statistics, measurements measurement assessments, structural estimates, and bootstrap intervals (Chen, 2023). The materials provided did not contain individual response records. By extension, the analysis might be verified to be consistent with reported tables, but the initial estimation was not reproducible using raw observations.

The questionnaire will be designed based on the last experience of the respondents regarding Travel recommendation based on AI. Instrument examples

would be AI chatbots, smart travel planning apps and AI enabled booking platforms. The mentioning of a recent experience offers a context of a common response across the construct items. However, the sites vary in terms of functionality and information sources. The design thus examines perceptions in a wide range of recommendation services. It does not make comparisons of specific providers, algorithms, interfaces or methods of recommendation generation. The conclusions platform-specific would need more in-depth observations than the provided summaries.

**Eligibility and analytical sample**

There are three conditions of eligibility in the proposed screening instrument. The respondents must be the age of eighteen and must have been using or read AI based travel suggestions within the last twelve months and must have planned, booked, or traveled one or more trips, during that time. The workbook records 560 responses out of which 560 were eligible responses and 0 excluded responses. These numbers form the analytical sample of the model mentioned. They fail to set a population response rate since the number of persons approached/ invited is not available (Mimansha Patel & Nitin Patel, 2019). Nor does the lack of exclusions confirm that all the possible data quality issues were considered individually.

The plan sets a provisional recruitment goal 550 and clearly differentiates that goal and a statistically set minimum. There are ten other records of analysis that the workbook reports. The current paper adopts the given end count of 560 instead of considering the planning target as the sample achieved. The supplied materials do not specify recruitment channels, sampling frame, collection dates, geographic coverage or the original process of data generation. In this regard, the probability sampling and national representativeness are not asserted. The use of the Bangladeshi taka used in the income question is contextual information regarding the instrument yet does not verify independently of the residence or the nationality of the analytical cases.

**Measurement instrument**

There are ten demographics and travel questions and twenty statements in the questionnaire. There are five indicators per construct. Measures of recommendation quality include perceived accuracy, relevancy, descriptiveness, consistency to user criteria and clarity (Andiappan & Wan, 2020). Personalization entails preferences to destinations, financial constraints, activities and interests, times and time span, and special needs. Dependability, credibility, suggestions, reliability in comparison and integrity falls under trust. Decision making in tourism includes destination, alternative, service choice, informed judgement and determination of the final decisions. There is a five-point scale of responses; strongly disagree and strongly agree.

Each of the four constructs is stipulated to be reflective in the provided model. Indicators under this specification are expressions of a shared perception behind them. Their analysis is thus based on indicator loadings, internal consistency, convergent and discriminant validity. This method is suitable to the given interpretation of measurement, still, it does not address all the potential conceptual issues. Certain dimension attributes of recommendation can also be considered as separate dimensions (Mellenbergh *et al.*, 2003). The development of instruments in the future might explore that option. The current analysis retains the provided reflective specification and assesses the claim of this separation by the four constructs based on the reported results of measurement.

**Analytical strategy**

The given analysis employed partial least squares structural equation modelling to estimate the joint measurement and structural relationships. The analysis was done using descriptive statistics, outer loading, reliability coefficients, average variance extracted, and discriminant validity diagnostics (Adaikkalam Zabihi *et al.*, 2025). Structural analysis took into account predictor collinearity, explained variance, direct effects, indirect effect, and total effect. The workbook states 5,000 bootstrap resamples and range between 2.5th and 97.5th percentiles. The support of the hypothesis is mainly assessed by the 95% interval described being in the expected direction and not necessary including zero. Probability values that are reported are left in their original form instead of being turned to zero.

Cronbach alpha, rho A, and composite reliability were used to determine internal consistency. Standardized loadings and average variance extracted were used to assess convergent validity. The heterotrait monotrait ratios, cross loadings and bootstrap intervals of heterotrait monotrait ratios were used to test discriminant validity. These diagnostics were read jointly. Structural variance inflation factors determine overlap of predictors of the same endogenous construct. Varce factors of indicators were also obtained, although they were not considered as evidence that common method bias did not occur. The workbook lacks an independent procedural or statistical evaluation that could prove the outliving of that bias.

The R2 and adjusted R2 is used to explain the variance. Effects sizes indicate the incremental explanatory value of each predictor in its structural equation. The evaluation of indirect effects was not based on the determination of significant components paths but evaluated directly based on their bootstrap intervals. Additive effects are a combination of direct and indirect coefficients reported (Mimansha Patel & Nitin Patel, 2019). No out of sample prediction test, holdout test, global fit test as well as longitudinal verification data were provided. To this end therefore, the analysis covers measurement performance and explanatory associations in the given sample. It fails to determine predictability of new tourists or the relative strengths of competing recommendation systems.

**Ethical scope and reporting transparency**

This questionnaire has been introduced by stating the fact that it is voluntary, responses are confidential and that the information is only going to be used in academic context. The following are statements that outline participant communication. The provided materials do not record real consent process, ethics review process, data storage, and pilot testing (Chen, 2023). The manuscript thus does not suggest that such practices took place. Such difference is required due to the fact that a completed analytical workbook and a finalized questionnaire can offer diverse types of evidence. Good statistical outcomes cannot be used to deduce the ethical approval, fieldwork authenticity, and respondent consent. The results are given within the frame of presentations possible within the context of its documentation.

## RESULTS AND DISCUSSION

### Sample characteristics

The analytical sample includes 560 cases that are eligible and twenty indicators at four constructs. Between eighteen and twenty-four is 31.79% and between twenty-five and thirty-four is 36.61%. The combination of these categories makes up 68.39% of the sample. The rest of the groups are thirty-five to forty-four at 18.04%, forty-five to fifty-four at 9.29% and fifty-five or above at 4.29%. The number of male respondents is 51.25% and that of female respondents is 46.43%. Other gender reactions and unreported reasons take 1.61% and 0.71 %, respectively. The distributions capture the provided sample and they are not used to determine the composition of the larger tourist population.

The cases of undergraduate education stand at 50.00% whereas postgraduate education is at 24.82%. The greatest occupational category (32.14%) is composed of private employees and students (24.11%) occupy the second and third place. The two lowest stated categories of income (incomes) combined constitute 53.57%. Travelling with the purpose of leisure is the leading purpose of travel 67.14% and domestic travelling is the most recently planned purpose of travelling 67.50%. The majority of the cases indicate a single or two trips in the last twelve months. The combination of AI chatbots and AI enabled booking platforms represents 68.57% of primary sources of recommendations. These results are supposed to be informed by the concentration of younger and relatively educated users on the interpretation of the total structural estimates.

**Table 1:** Sample demographic and travel profile

| Characteristic | Category | n | % |
|---|---|---|---|
| Age | 18–24 | 178 | 31.79 |
| Age | 25–34 | 205 | 36.61 |
| Age | 35–44 | 101 | 18.04 |
| Age | 45–54 | 52 | 9.29 |
| Age | 55 or above | 24 | 4.29 |
| Gender | Female | 260 | 46.43 |
| Gender | Male | 287 | 51.25 |
| Gender | Other | 9 | 1.61 |
| Gender | Prefer not to say | 4 | 0.71 |
| Education | Higher Secondary | 100 | 17.86 |
| Education | Other | 14 | 2.50 |
| Education | Postgraduate | 139 | 24.82 |
| Education | Secondary | 27 | 4.82 |
| Education | Undergraduate | 280 | 50 |
| Occupation | Businessperson | 60 | 10.71 |
| Occupation | Government Employee | 78 | 13.93 |
| Occupation | Other | 32 | 5.71 |
| Occupation | Private Employee | 180 | 32.14 |
| Occupation | Self-Employed | 75 | 13.39 |
| Occupation | Student | 135 | 24.11 |
| Monthly income BDT | 20,000–39,999 | 138 | 24.64 |
| Monthly income BDT | 40,000–59,999 | 122 | 21.79 |
| Monthly income BDT | 60,000–79,999 | 62 | 11.07 |
| Monthly income BDT | 80,000 or above | 53 | 9.46 |
| Monthly income BDT | Below 20,000 | 162 | 28.93 |
| Monthly income BDT | Prefer not to say | 23 | 4.11 |

| | | | |
|---|---|---|---|
| Trips in past year | 1–2 | 347 | 61.96 |
| Trips in past year | 3–4 | 146 | 26.07 |
| Trips in past year | 5–6 | 50 | 8.93 |
| Trips in past year | More than 6 | 17 | 3.04 |
| Travel purpose | Business | 47 | 8.39 |
| Travel purpose | Education | 42 | 7.50 |
| Travel purpose | Leisure | 376 | 67.14 |
| Travel purpose | Other | 11 | 1.96 |
| Travel purpose | Visiting Friends or Relatives | 84 | 15 |
| Travel type | Both | 87 | 15.54 |
| Travel type | Domestic | 378 | 67.50 |
| Travel type | International | 95 | 16.96 |
| Recommendation source | AI-Enabled Mapping or Discovery Application | 47 | 8.39 |
| Recommendation source | AI-Enabled Travel Booking Platform | 188 | 33.57 |
| Recommendation source | AI Chatbot | 196 | 35 |
| Recommendation source | AI Travel Planning Application | 110 | 19.64 |
| Recommendation source | Other | 19 | 3.39 |
| Use frequency | Frequently | 118 | 21.07 |
| Use frequency | Occasionally | 146 | 26.07 |
| Use frequency | Rarely | 73 | 13.04 |
| Use frequency | Sometimes | 167 | 29.82 |
| Use frequency | Very Frequently | 56 | 10 |

*Note: Percentages may differ slightly from 100 because of rounding. n = 560.*

The distribution of use frequency is not concentrated amongst a few intensive users, but spread across various categories. Sometimes accounts for 29.82%, occasionally for 26.07%, frequently for 21.07%, rarely for 13.04%, and very frequently for 10.00%. This variation suggests that the available records reflect varying levels of exposure reported. Use frequency is however not a control or moderator in the model. The potential relationships thus provide an overview of the cumulative sample. They fail to determine whether the trust works in a similar fashion between occasional and frequent users. These comparisons would entail group specific measurement evaluation and structural estimation in addition to the workbook presented.

**Descriptive statistics**

Construct meanings are averagely outside the scale middle. The mean of recommendation quality is 3.2450 and the standard deviation of 0.9676. The mean and standard deviation of personalization are 3.2075 and 0.9555 respectively. The mean of trust is 3.2407 and the standard deviation of trust is 0.9348. The mean and standard deviation of tourist decision making is 3.2479 and 0.9646 respectively. These minor variations in these means should not be regarded as statistically determined rankings since no paired comparison is given. Their main descriptive implication is that positive ratings exist without the close to universal assent that would be indicated by means around five.

**Table 2:** Construct descriptive statistics

| Construct | n | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| ARQ | 560 | 3.2450 | 0.9676 | 1 | 5 |
| PER | 560 | 3.2075 | 0.9555 | 1 | 5 |
| TR | 560 | 3.2407 | 0.9348 | 1 | 5 |
| TDM | 560 | 3.2479 | 0.9646 | 1 | 5 |

*Note: ARQ = recommendation quality; PER = personalization; TR = trust; TDM = tourist decision making.*

The indicator ranges between 3.0786, which is recommendation clarity, and 3.3661, which is perceived integrity. Each indicator makes use of the entire range of responses between one to five. There are a range of indicator standard deviations 1.1025 to 1.1840, which reflect a variation about the average response. The descriptive results consequently do not include either a homogenous pattern of response or a constraint to the highest response categories. Construct skew is slightly negative, with values of between minus 0.1697 and minus

0.2591. There is also negative excess kurtosis between constructs. These summars depict shape of distributions, yet they never determine on their own the lack of careless reacting, duplicated records or any other case level quality issues.

**Indicator reliability and convergent validity**

The twenty fixed outer loadings are all greater than the reference of workbook of 0.708. The loadings of the recommendations are between 0.8216 and 0.8601. The loadings of personalization are between 0.7898 and 0.8790. Trust loadings range from 0.7891 to 0.8621. The loading of tourist decision making is between 0.8039 and 0.8570. All the reported loading intervals do not include zero. The findings justify retaining all the provided indicators in the reflective specification. None of the items has to be removed based on the reported loading criterion. The conclusion is about the statistical indicator performance and is not a substitution of a substantive evaluation of wording or content covered.

**Table 3:** Standardized indicator loadings

| Construct | Indicator | Loading | 95% interval |
|---|---|---|---|
| ARQ | ARQ1 | 0.8517 | 0.8256–0.8755 |
| ARQ | ARQ2 | 0.8226 | 0.7923–0.8500 |
| ARQ | ARQ3 | 0.8601 | 0.8345–0.8828 |
| ARQ | ARQ4 | 0.8216 | 0.7898–0.8495 |
| ARQ | ARQ5 | 0.8535 | 0.8281–0.8765 |
| PER | PER1 | 0.8660 | 0.8436–0.8863 |
| PER | PER2 | 0.8232 | 0.7892–0.8517 |
| PER | PER3 | 0.8790 | 0.8586–0.8970 |
| PER | PER4 | 0.7898 | 0.7513–0.8211 |
| PER | PER5 | 0.8438 | 0.8163–0.8679 |
| TR | TR1 | 0.8431 | 0.8176–0.8648 |
| TR | TR2 | 0.8341 | 0.8044–0.8596 |
| TR | TR3 | 0.8621 | 0.8402–0.8821 |
| TR | TR4 | 0.7891 | 0.7540–0.8197 |
| TR | TR5 | 0.8418 | 0.8160–0.8642 |
| TDM | TDM1 | 0.8570 | 0.8327–0.8781 |
| TDM | TDM2 | 0.8314 | 0.8055–0.8552 |
| TDM | TDM3 | 0.8497 | 0.8231–0.8724 |
| TDM | TDM4 | 0.8039 | 0.7693–0.8336 |
| TDM | TDM5 | 0.8546 | 0.8314–0.8753 |

Cronbach's alpha ranges from 0.8908 to 0.8975. Composite reliability ranges from 0.9197 to 0.9241, while rhoA ranges from 0.8934 to 0.9012. These findings show high internal consistency of each construct. The variance extracted by averaging the recommendations is 0.7091 which represents the quality of recommendation, 0.7072 which represents personalization, 0.6962 which represents trust and 0.7048 which represents decision making. Each value exceeds 0.50. The latent construct therefore explains over half of the variance explained in its indicators in the provided measurement model. Substantial loadings and acceptable average variance extracted are a demonstration of convergent validity in this analysis.

**Table 4:** Internal consistency and convergent validity

| Construct | Alpha | rhoA | rhoC | AVE |
|---|---|---|---|---|
| ARQ | 0.8975 | 0.9005 | 0.9241 | 0.7091 |
| PER | 0.8962 | 0.9012 | 0.9234 | 0.7072 |
| TR | 0.8908 | 0.8934 | 0.9197 | 0.6962 |
| TDM | 0.8952 | 0.8965 | 0.9227 | 0.7048 |

*Note: rhoC denotes composite reliability. AVE denotes average variance extracted.*

**Discriminant validity**

The heterotrait monotrait ratios are between 0.4321 and 0.7063. The greatest one is between trust and tourist decision making, which is in line with their relatively high level of association in the structural framework. However, it is still lower than the conservative reference value of the workbook, 0.85. Bootstrap upper bounds are 0.4985 to 0.7568 with all of them not including one. These results support the empirical separation of the four constructs. Trust and decision making are implicated, and their indicators do not act like they are an unidentifiable construct as reported diagnostics.

**Table 5:** Discriminant validity and bootstrap intervals

| Construct pair | HTMT | 95% interval |
|---|---|---|
| ARQ and PER | 0.4321 | 0.3608–0.4985 |
| ARQ and TR | 0.5440 | 0.4695–0.6130 |
| ARQ and TDM | 0.5620 | 0.4918–0.6271 |
| PER and TR | 0.5392 | 0.4713–0.6025 |
| PER and TDM | 0.5428 | 0.4675–0.6096 |
| TR and TDM | 0.7063 | 0.6526–0.7568 |

The Fornell Larcker matrix gives a congruent additional outcome. Recommendation quality, personalization, trust, and decision making have the square roots of average variance of 0.8421, 0.8410, 0.8344, and 0.8395 respectively. Each of them is greater than the respective reported correlations with other constructs. Cross loadings also indicate that all indicators load strongest on constructs they are assigned. These results bolster the trust in perceiving the structural paths as networks between identifiable perceptions. Empirical separation, however, does not mean an absolute conceptual dissociation. The quality of recommendations, personalization and trust are also related to the same reported recommendation experience.

**Collinearity and explanatory performance**

The factors of structural variance inflation are between 1.1781 and 1.5168. The predictors of trust each have a value of 1.1781. In the equation of decision making, the values of the recommendation quality, personalization and trust are 1.3691, 1.3593, and 1.5168 respectively. These values are not indicative of problematic overlap according to the criteria of references given in the workbook. The variance inflation factors of indicators vary between 1.8809 and 2.6564. These structural results thus seem to be interpretable without any significant inflation due to the measured predictor correlations. This test tackles the issue of collinearity and should not be confused with more general statements of bias or model correctness.

The adjusted R2 is 0.3384, and the model accounts 34.07% of the variance of trust. The 47.88% of the variation in tourist decision making can be attributed to recommendation quality, personalization and trust with an adjusted R2 of 0.4759. The fact that the difference between every unadjusted and adjusted value is small is an indication of a small adjustment of the number of predictors in comparison to the sample size. The model has a significant explanatory coverage but there is still a lot of variances that the model does not explain. Specifically, over one-half of the decision-making variance is beyond the stated relationships. The reported values of the R2 describe sample explanation and they are not to be viewed as the indicator of predictive power of new observations.

**Table 6:** Explained variance

| Outcome | $R^2$ | Adjusted $R^2$ | Predictors | n |
|---|---|---|---|---|
| TR | 0.3407 | 0.3384 | 2 | 560 |
| TDM | 0.4788 | 0.4759 | 3 | 560 |

Effect sizes can show that the recommendation quality and personalization contribute medium to trust, the f 2 values are 0.1621 and 0.1538. Their direct contribution to decision making is less, 0.0670 and 0.0538. There is a moderate contribution of trust to decision making 0.2352. This pattern is a complement to the path coefficients in that it reveals that trust contributes the most incremental explanatory value to the decision equation. The finding is not sufficient to prove that trust is the sole significant design objective. The contribution of both antecedents is both direct and indirect and the pragmatic inferences of the change of a system are not able to be determined solely by skillful associations.

**Table 7:** Incremental effect sizes

| Predictor | Outcome | $f^2$ | Magnitude |
|---|---|---|---|
| ARQ | TR | 0.1621 | Medium |
| PER | TR | 0.1538 | Medium |
| ARQ | TDM | 0.0670 | Small |
| PER | TDM | 0.0538 | Small |
| TR | TDM | 0.2352 | Medium |

**Direct hypothesis tests**

There is a positive relationship between recommendation quality and trust and 95% interval of 0.2825 to 0.4277. Trust is also positively related with personalization with $\beta = 0.3456$ and the range of 0.2795 to 0.4106. The H1 and H2 are thus supported. These two coefficients are of similar magnitude although their difference has not been tested formally. The results justify the existence

of both relationships instead of stating that one of the antecedents is unquestionably more important. The fact that their intervals overlap is also inadequate alone to create equality between the population coefficients.

The recommendation quality has a positive direct correlation with post-personalization and trust decision making. The coefficient is 0.2186, with a 95% interval from 0.1451 to 0.2891, supporting H3. Personalization has a positive direct correlation as well, with β = 0.1953 and a 0.1233 to 0.2646 interval value, in favor of H4. These coefficients suggest that the information evaluation, as well as preference alignment, can still be of importance outside their relationship with trust. They are not percentage changes in decisions or probability of booking increases. They are both standardized structural coefficients included in the provided model.

The decision-making equation has the highest direct coefficient with trust. Its standardized association is 0.4312, with a 95% interval from 0.3663 to 0.4987, supporting H5. The probability of the bootstrap of each of the direct paths is reported as 0.0004. The consistently small values must be read along with the magnitude of effects and uncertainty levels. The fact that a relationship is statistically significant does not imply that all relationships are equally substantively important. The higher coefficient and incremental effect size of trust determine its relatively strong role in this specification and the practical contribution of interventions remains open.

**Table 8:** Direct structural relationships

| H | Path | β | t | p | 95% interval |
|---|---|---|---|---|---|
| H1 | ARQ → TR | 0.3548 | 9.5762 | 0.0004 | 0.2825–0.4277 |
| H2 | PER → TR | 0.3456 | 10.3794 | 0.0004 | 0.2795–0.4106 |
| H3 | ARQ → TDM | 0.2186 | 5.9565 | 0.0004 | 0.1451–0.2891 |
| H4 | PER → TDM | 0.1953 | 5.4022 | 0.0004 | 0.1233–0.2646 |
| H5 | TR → TDM | 0.4312 | 12.6917 | 0.0004 | 0.3663–0.4987 |

*Note: All hypotheses are supported. β is standardized. Intervals are the reported 95% bootstrap intervals based on 5,000 resamples.*

**Indirect effects and total effects**

The indirect relationship between the recommendation quality and decision-making using trust is 0.1530 95% interval (0.1143- 0.1967). The indirect relationship between personalization and trust is 0.1490 with a range between 0.1161 and 0.1858. The two intervals are non-zero and in favour of H6 and H7. Since the associated direct coefficients are positive and upheld, the trend is in line with complementary partial mediation. Trust is statistically significant and it does not supplant the direct relationships but adds a positive relationship. Figure 2 shows the standardized direct coefficients, as well as value of explained variance of the provided structural diagram. The total effects are 0.3716 in terms of recommendation

**Table 9:** Indirect relationships through trust

| H | Path | β | t | p | 95% interval |
|---|---|---|---|---|---|
| H6 | ARQ → TR → TDM | 0.1530 | 7.1968 | 0.0004 | 0.1143–0.1967 |
| H7 | PER → TR → TDM | 0.1490 | 8.3407 | 0.0004 | 0.1161–0.1858 |

*Note: All hypotheses are supported. β is standardized. Intervals are the reported 95% bootstrap intervals based on 5,000 resamples.*

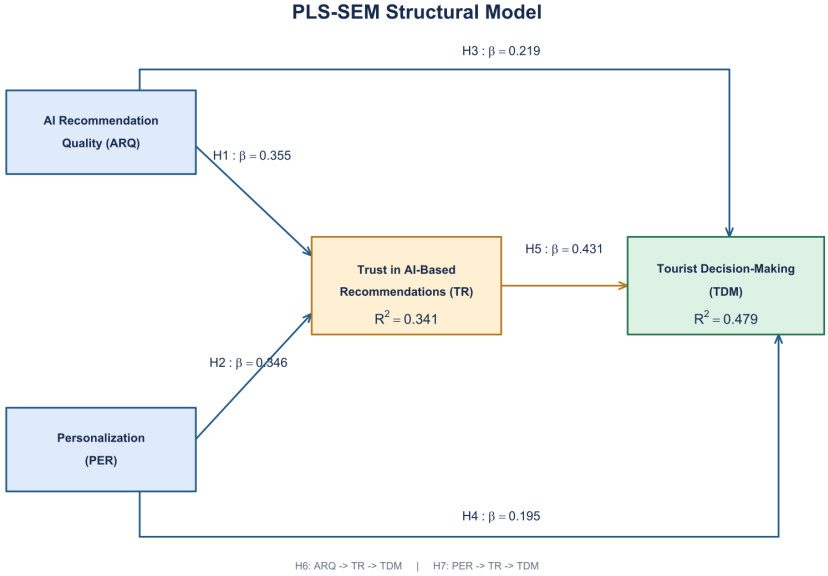



**Figure 2:** Structural model with standardized coefficients and explained variance

quality and 0.3443 in terms of personalization. Their 95% intervals are 0.3006 to 0.4398 and 0.2710 to 0.4147, respectively. The overall coefficients are the same as the direct and indirect effects reported, with rounding. The indirect components, as descriptive computations, are about 41.2% and 43.3% of their total coefficients. The decomposition of the model is summed up by these ratios. They are not approximations of the share of actual travel choices that is brought about by trust, and they do not determine the extent of decision making that would be different given the experimental manipulation of confidence.

**Table 10:** Total associations with decision making

| Path | Total β | t | p | 95% interval |
|---|---|---|---|---|
| ARQ → TDM | 0.3716 | 10.3385 | 0.0004 | 0.3006–0.4398 |
| PER → TDM | 0.3443 | 9.5468 | 0.0004 | 0.2710–0.4147 |

## Discussion

### Interpreting recommendation quality

The positive correlation between quality of recommendation and trust implies that trust is related to perceived performance of recommendation outputs. Tourists that report more relevant, accurate, detailed, consistent and clear information also report greater trust. The outcome favours a reading where reliable data give a ground to trust. It does not exclude mutual perception as well. Respondents who have already placed their trust in a system can put its outputs into higher ratings. The design that is available is not able to discriminate between these sequences (Xu *et al.*, 2021). The substantive conclusion is thus that there exists a positive relationship between quality and trust in the analysis provided, and quality still has an independent influence on perceived decision support.

The direct quality coefficient suggests that good information may be of help in making decisions other than the one associated with trust. This difference is important to the interpretation of recommendation services. An obvious comparison of travelling options can aid planning even though the traveller is sceptical of the platform. Even information without generating full confidence might be useful in practice (Cheng, 2021). On the other hand, trust that lacks information to use may only be of limited help when it comes to choosing destinations and services. The direct and indirect paths that are observed are consistent with the two considerations. They are in favor of a model whereby informational contribution and the confidence pathway are complementary aspects of reported decision assistance.

### Interpreting personalization

The trend of personalization resembles that of recommendations. Its positive correlation with trust implies that the perceived responsiveness to personal situations is linked to trust in the system. Budget, interest, schedule, and other specific needs-based recommendations might seem more reliable since they tackle an identifiable planning issue. The close association with decision making implies an added input of practical suitability. Preference alignment can eliminate the irrelevant alternatives and ease the comparison of the alternatives (Sánchez-Ancajima, 2023). The interpretations comply with the measured constructs, but the given analysis does not see the real order of filtering, evaluation and choice.

The findings are not to be construed to favour unhindered personalization. The tool judges that outputs meet needs, but not that a lot of data gathering is good. It also makes no evaluation of whether customized alternatives maintain an adequate degree of diversity or whether suggestions make earlier decisions overly powerful. The relationship being supported is that which relates to perceived alignment in the provided records. The next generation analysis needs to differentiate between the quality of personalization and intensity of personalization (Cepeda-Pacheco & Domingo, 2022). A highly individualized yet poorly responding system can be created, as well as a set of well-defined requirements that can give useful and acceptable recommendations.

### Trust as an explanatory mechanism

The strongest direct predictor of decision making in the model reported is trust with positive indirect correlations with both antecedents. This trend recognizes that confidence is a key explanatory relationship between ratings of recommendation performance and reported planning assistance (Fudholi *et al.*, 2021). It also demonstrates why considering trust as a last product of system quality would give an incomplete view. The perceived utilization of recommendations in destination evaluation and service choice is linked to trust. Its findings justify its coverage as a middle ground construct and the cross-sectional design imposes a tight rein on the use of language related to time and cause.

The result of the partial mediation also averts the overly precise conclusion. Trust takes all the relationship between the antecedents and decision making. Quality and personalization have direct coefficients that are direct and their overall impact is greater than the respective direct impacts (Gu *et al.*, 2020). The practical usefulness of information and the suitability of recommendability along with confidence should therefore be taken into account in system development. A seemingly credible interface that makes weak comparisons can result into an undeveloped direct contribution. The indirect pathway may not be developed because of an informative interface that users find unreliable. According to the model, the above dimensions are linked to various aspects of the same reported decision support process.

### Measurement and contextual interpretation

The results of the measurements offer a consistent

foundation over which to identify the four constructs. Interpretation of the structural relationships is supported by substantial loadings, high internal consistency, reasonable extracted variance and reasonable diagnostics of discriminant validity (Solakis *et al.*, 2024). However, there is still the dependence of performance of statistical measurement on the records and the specification of the model supplied. Common evaluation patterns may include similar expressions of the item, shared background context of response, and using a single response scale. These possibilities are not solved separately in the current workbook (Yan, 2022). The results do not) lend credence to internal measurement adequacy without drawing a conclusion that all sources of response bias have been eradicated.

The meaning of the pooled estimates is also dependent on the sample profile. Substantial proportions of the analytical cases are covered by younger respondents, undergraduate or postgraduate education, leisure travellers, and domestic travel planners (Zhou *et al.*, 2021). Their experiences might not be as those of the older traveller, the less frequent internet user, or one who plans complicated international trips. Also, users of chatbots and users of booking platforms might have varying recommendation processes. Since the model presented combines these groups, the result explains their overall trend. Possessions of group differences, media superiority or prevalence in a population would go beyond the provided evidence.

## Implications

### Conceptual implications

The research advocates a model that isolates the quality of output, agreement on preference, trust, and perceived decision-aid. These are constructs which are related to each other and empirically different in the given model. The differentiation explains why positive system appraisals may possess an additional relationship with travel decisions. It may have a direct impact on quality and customization and make the information useful and the alternatives applicable (Erbil & Wörndl, 2022). They can play an indirect role as well by trust. The complementary mediation pattern thus gives a more detailed account than an undivided measure of favourable attitudes towards artificial intelligence-based recommendations.

The findings also differentiate causal importance and explanatory strength. The direct coefficient of trust is the largest, but the model does not give the increase in the trust as the necessary take place to achieve the highest impact on the actual decisions. Several constructs might be impacted concurrently by unmeasured risk perceptions, prior experience, digital skills, or satisfaction. Likewise, the overall impacts of quality and personalization cannot be converted into operational returns without further evidence. The experimental contribution is based on the idea that it has recognized a pattern of associations that are supported, which can be studied in the future more directly by longitudinal and experimental research.

### Implications for recommendation design

The information that must be examined by the provider of Recommendation must be on the level of the travel decision being supported. Checks of accuracy should touch on the details of the destination and conditions of service. The completeness should be evaluated as compared to the data required to compare plausible options. Clarity It should enable the tourists to know the reasons why an option is recommended (Lee *et al.*, 2022). The practices are based on the measured quality dimensions, but their effectiveness was not assessed as interventions. Providers might measure them by some controlled variation, which measures perceived quality and independent observed decision outcomes. This type of evaluation would relate the current explanatory model to quantifiable enhancements in the service performance. The parameters of personalization must enable travellers to declare and update their budgets, schedules, activities, and particular needs. Relevant constraints should be revealed in a recommendation to allow users to recognize the faulty assumptions. This method is in line with the positive correlations obtained with preference congruence. But the evidence is not dictative of how many preference questions are best and to what extent those ought to be automated. Empirical testing is to check whether personalization decreases irrelevant options and maintains a sensible choice (Fan & Zhang, 2022). It would also need to take into account the ability of the system to be corrected by the end-users without considerable effort when their situations vary.

Design connected with trust should be stressed on justified trust. The source of information, doubt, business connection, and the foundation of advice might influence the way in which tourists perceive dependability of a system. The present model did not independently measure these features and are only proposed applications as opposed to observed effects. Their analysis must be able to differentiate between confidence and blind trust. An effective concierge service ought to assist tourist in knowing when further authentication is required. Greater trust is only useful to the extent that it is adequate to the trustworthiness of the information underlying it, and the impact of the given decision.

### Implications for tourism services

The framework can guide tourism organizations in evaluating the links between recommendation experiences and various planning activities. The destination discovery, alternative comparison, service selection and itinerary finalization might need different information. These stages can be masked with one general measure of satisfaction (Zhou *et al.*, 2022). The five items of decision making offers a beginning framework of studying the perceived assistance throughout the process. Such perceptions could be matched with observable characteristics in future service evaluation including accuracy of comparison, time taken to do so, number of times the patient corrects, and appropriateness of chosen

alternatives. Such measures would widen the current research to self-reported assistance.

Variation in user experience should also be identified in training and customer support. Interpretation of recommendation functions may need to be explained to occasional users more clearly and powerful mechanisms of revising constraints and comparing alternatives are required by frequent users. Those differences between groups are not represented in the provided results, but the sample distribution shows them as the questions that should be addressed to evaluate the services (Arefieva *et al.*, 2023). Support materials may be experimented with regards to contribution to understanding and proper dependency. It should aim at an informed planning process where suggestions can be subjected to checks and visitors have substantial influence on end-decision making.

## CONCLUSION

The provided analysis confirms the positive correlations between recommendation quality, personalization, trust, and tourist decision making. Bootstrap intervals that exclude zero support all five direct hypotheses as well as the two indirect hypotheses. The decision equation has the greatest direct coefficient with trust. The quality of recommendations and personalization have positive direct correlations and positive indirect correlations based on trust. The resultant pattern is in line with a complementary partial mediation. The model describes 34.07 percent of the trust variance and 47.88 percent of decision-making variance in the 560 records of analysis.

The substantive implication has it that helpful travel suggestions have a combination of reliable information, compatibility with personal needs, and trust in those providing the recommendations. All these dimensions play a role in the various aspects of the proposed explanatory process. Such results give a narrow-minded ground of subsequent review of recommendation services. The empirical breadth of their study is limited by the paperwork provided, failure to verify the raw data and using cross sectional perceptions. Stronger causal, population or operational conclusions can be maintained only by confirmation with documented fieldwork and independent behavioural evaluation.

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