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Beyond Passive Observance: Understanding Egyptian Domestic Tourists' Behaviour through Hyper-Personalised Digital Clienteling

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Abstract

This study investigates the impact of hyper-personalisation through digital clienteling on the online booking intentions and behaviours of domestic tourists, employing an integrated model of the Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA). Conducted through a quantitative methodology, the study gathered responses from 326 participants through a structured questionnaire. The participants were randomly chosen from various Egyptian Facebook travel groups, specifically targeting individuals with prior experience in online booking for domestic vacations. The analysis of the gathered data was carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS 4.

The findings reveal a satisfactory fit for the model, with significant relationships between attitude, subjective norms, perceived ease of use, perceived usefulness, and online booking intention and behaviour. The demographic analysis highlights a prevalence of educated and younger participants, suggesting that hyper-personalised digital clienteling may appeal more to this demographic.

Practical implications suggest targeted marketing efforts and optimised digital platforms to enhance the user experience. Theoretical implications contribute to the advancement of technology adoption models, providing insights into tourists' decision-making processes. The study's originality lies in its focus on the Egyptian context and domestic tourism market, enriching the literature on technology adoption in developing countries.

Keywords: hyper-personalisation, digital clienteling, online booking, domestic tourism, TAM, TRA, technology adoption, big data, customer behaviour, Egypt.

1. Introduction

The integration of information technology into tourism enterprises, encompassing marketing, demand management, forecasting, service and performance management, as well as information sharing and collaboration, contributes significantly to well-informed decision-making (Liu et al., 2015). In the present day, tourists utilise technology for destination exploration, trip planning, and transactions (Pinto and Castro, 2019). To adapt to this trend, tourist businesses are embracing digital transformation and e-business (Dredge et al., 2018). However, only a limited number have effectively navigated the intensifying competition driven by evolving business models (Wade, 2015). In the pursuit of stronger customer connections, businesses are focusing on delivering high-quality services and restructuring their operations through digital transformation to engage customers across

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diverse digital platforms (Kalia and Paul, 2021). Digital transformations yield innovations and profits for companies (Jain et al., 2021). According to Aboushouk and Elsawy (2020), a key aspect of achieving high performance in digital business is leveraging abundant data and analytics for decision-making, innovation, and development. Without this capability, companies risk stagnation (Arya et al., 2019). Around 90% of individuals use smartphones and various platforms to access detailed service information, hence, it is essential for companies to create services tailored to meet the specific requirements of their customers (Paul, 2019). For over five decades, experiences have been central to tourism production and research, with the creation of positive experiences deemed essential in the tourism industry. Personalisation facilitates efficient access to customized information for customers, providing businesses with a means to establish robust consumer relationships (Ashqar et al., 2023). According to Valdez Mendia and Flores-Cuautle (2022), personalisation is a company's capacity to treat customers individually through personal messaging, targeted banner ads, special bill offers, or other personalised transactions.

Traditional data collection methods, like surveys and feedback forms, lack relevance in fast-paced interactions. Online users avoid sharing personal information through lengthy surveys and feedback forms (Jain et al., 2018). To provide a unified customer experience, businesses must empathise with customers, identifying pain points and curating products aligned with their lifestyle, choices, and past interactions. This contrasts with the outdated push strategy of generic offers. Nowadays, understanding and addressing customer complexities involves utilising technology-driven solutions based on customer inputs, search engine records, virtual communication data, and behavioural insights (Jain et al., 2018). Companies should embrace digital clienteling, establishing automated relationships with customers, and ensuring consistent solutions across multiple touchpoints. Digital clienteling is defined as enhancing customer engagement through a unified customer information resource (Jain et al., 2021). A unified model for accessing the latest customer information is crucial, and digital clienteling emerges as a viable solution. Digital transformation through digital clienteling provides a unified resource of customer information, capturing extensive volumes of structured, unstructured, behavioural, and transactional data generated by customers (Erevelles et al., 2016). It offers personalised experiences, seamless integration, unified data, and channel engagement, enhancing customer response and retention. Employing a real-time data approach shapes the shopping experience into a hyper-personalised journey (Hart, 2016). Hyper-personalization has transformed the business model for retailers by offering tailored solutions based on customer data. Customers engaging with hyper-personalised product options through digital clienteling show positive interactions, leading to a high probability of purchase (Jain et al., 2021). Recently, hyper-personalisation techniques have swiftly reshaped the public domain through digital platforms (Ng, 2020).

Various previous studies highlighted a gap in the area of technology acceptance, usage, and impact on tourism in developing countries and emphasised the importance of investigating different stakeholders' perspectives, including tourists (e.g., Hassan et al., 2022; Elsawy, 2023; M. Elsawy and Eltayeb, 2023). Moreover, the existing literature emphasises the growing significance of digital transformations in the tourism industry, particularly with the adoption of hyper-personalisation through digital clienteling for online bookings. However, there is a notable gap in understanding the nuanced factors influencing online booking intention and behaviour for domestic vacations, particularly from the perspective of domestic tourists in developing countries. To the best of the author's knowledge, no previous study addressed domestic tourists' behaviour through hyper-personalised digital clientele. Furthermore, studies like Hefny (2021) emphasised the escalating trend of online bookings in Egypt, underscoring the significance of exploring the intentions of Egyptian customers regarding online travel service bookings.

Building on the previous introduction and integrating two theories, the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA), this study attempts to answer the following questions:

Q1. What factors contribute to the online booking intention of domestic tourists when exposed to hyper-personalisation using digital clienteling?

Q2. To what extent does the hyper-personalisation of digital clienteling impact the decision-making process during online bookings for domestic vacations?

These questions aim to explore the unique dynamics of hyper-personalisation through digital clienteling in the domestic tourism context, focusing on the intention and behaviour of domestic tourists during the online booking process.

2. Literature Review and Hypotheses Development

2.1 Digital Clienteling and Big Data

Stylos and Zwiegelaar (2019) highlighted that big data (BD) has significantly transformed business intelligence, particularly in dynamic, time-sensitive, and swiftly evolving businesses with unpredictable changes. Leveraging big data analytics is crucial for businesses aiming to offer personalised solutions and design products. Big data holds immense potential for enhancing customer service, executing online promotional marketing, and extracting insights from various channels to understand customer requirements (Chong et al., 2017). Its transformative power extends to effective decision-making and necessitates businesses revamping digital platforms, emphasising hyper-personalisation (Jain et al., 2018). However, most individuals working in the tourism sector, as per Belias et al. (2021), do not possess the necessary knowledge to understand and make use of applications related to big data.

Engaging customers across all channels, especially before, during, and after the booking experience, is essential for digital success. Businesses must bridge the gap between customer service expectations and delivery on the digital platform, emphasising the need for a comprehensive restructuring and redesign in the realm of digital shopping, focusing on hyper-personalisation (Jain et al., 2018). Omnichannel customer experiences, incorporating emotional and virtual elements throughout the shopping journey, are pursued by businesses. Clienteling, emphasising one-to-one marketing, fosters positive associations and customer loyalty through personalised communication (Jain et al., 2018). Big data analytics, relying on past customer search records from various sources, plays a pivotal role. This comprehensive information encompasses customer preferences, needs, buying history, patterns, and behaviour, allowing online retailers to provide hyper-personalised products and services (Jain et al., 2018).

2.2 Hyper-personalisation

Prior studies have explored the potential of technologies for personalised experiences, including the influence of smartphones on travel, the application of context-aware mobile apps in tourism, the use of high-tech for high-touch experiences, and the adoption of mobile tour guides for personalised routes and location-specific information (Ashqar et al., 2023). According to Saldanha et al. (2017), tourist organisations can enhance their market performance by utilising customers' active involvement in the business through the combination of technology and information systems. Here comes the role of hyper-personalisation, which involves utilising big data to deliver more specialised and personalised products, services, and information to targeted segments (Jain et al., 2018). This approach enables businesses to create an authentic online customer experience based on individual requirements. In the era of technology, customers seek to curate their surroundings according to their preferences, and they desire control over how they access information. Hyper-personalisation serves as a valuable tool for marketers to provide personalised information about customers, focusing on social listening, data analysis, and content. Simon (2014) highlights that NetfliX achieved a large amount of its rental customer business through the application of hyper-personalisation data. Online data collection allows companies to track customer purchase history, demographic information, ad clicks, and email subscriptions.

A hyper-personalisation strategy hinges on the organisation's ability to collect and convert customer data into personalised experiences (Valdez Mendia and Flores-Cuautle, 2022). Earlier research identified two personalisation goals: providing information tailored to specific individuals or groups at designated time intervals and enhancing revenue while reducing costs by employing a one-to-one marketing approach based on customers' needs, habits, lifestyle, preferences, likes, and dislikes (Valdez Mendia and Flores-Cuautle, 2022).

2.3 Theory of Reasoned Action (TRA)

The TRA is a widely used belief-based social cognitive theory in behavioural research (Song et al., 2021) and to predict behavioural intentions and actual behaviour in tourism studies (Plaza-Mejía et al., 2023; Ryu and Han, 2010). According to Jang and Cho (2022), TRA stands out as the most effective predictor of changes in human behaviour. Ajzen and Fishbein (1980) proposed that the Theory of Reasoned Action (TRA) elucidates an individual's intentions regarding their behavior. TRA comprises two key factors, namely attitude and subjective norms, that shape an individual's intentions towards a specific behaviour. Attitude represents the individual's behavioural beliefs, influencing changes in behavioural intentions, while subjective norms depict normative beliefs about a specific behaviour. Numerous previous studies, such as those by Jain et al. (2021), Jain et al. (2018), and McNeill & Moore (2015), have employed TRA to comprehend behavioural intentions related to omnichannel usage.

According to TRA (Ajzen & Fishbein, 1980; Davis, 1993), an individual's attitude significantly influences their behavioural beliefs regarding the use of technology and their adoption intentions. Moreover, the TRA posits that attitudes and subjective norms directly influence behaviour through the mediation of behavioural intention (Koo and Lee, 2018).

2.3.1 Attitude

Attitudes represent the overall inclination towards adopting or avoiding a particular behavior (Koo and Lee, 2018). According to the TRA model, individual intentions significantly influence buying behaviour (Ajzen and Fishbein, 1980). Attitude functions as a catalyst in the TRA framework, representing an individual's psychological inclination towards online shopping (Jahng et al., 2002). Attitude is manifested through behavioural beliefs, wherein an individual expresses a focal behaviour to gather information about a product or service. Subsequently, after obtaining information, there may be a desire to make a purchase. Several prior studies have substantiated the significance of attitudes as crucial predictors of intention (e.g., Fokides, 2017) Thus,

H1. Attitude towards hyper-personalisation using digital clienteling is positively related to online booking intention for a domestic vacation.

H2. Attitude towards hyper-personalisation using digital clienteling is positively and indirectly related to online booking behaviour for a domestic vacation.

2.3.2 Subjective norms

As per Ulker-Demirel and Ciftci (2020), subjective norms are individuals' normative beliefs about how others perceive or judge their involvement in a specific behavior, serving as a significant independent variable influenced by others in their buying behavior. According to

Ajzen and Fishbein (1980), they are a crucial determinant, reflecting social influence and perceived pressure and shaping purchasing intentions. Subjective norms indicate an individual's behaviour is influenced by their immediate social environment, such as friends, family, colleagues, and reference groups. Previous literature, including studies by Jain et al. (2021; 2018), establishes a positive relationship between subjective norms and planned behaviour. Given that human behaviour is driven by intentions, the impact of subjective norms is substantial (Karahanna et al., 1999). As per the theory, behavioural intention, a key reflection of actual behaviour, is influenced by an individual's subjective norms regarding the performance of that behaviour (Ulker-Demirel and Ciftci, 2020). Thus,

H3. Subjective norms regarding hyper-personalisation using digital clienteling are positively related to online booking intention for a domestic vacation.

H4. Subjective norms regarding hyper-personalisation using digital clienteling are positively and indirectly related to online booking behaviour for a domestic vacation.

2.4 Technology Acceptance Model (TAM)

The TAM, rooted in social psychology theories and introduced by Davis et al. (1989), is a valuable model for assessing the adoption of new technology by potential users. The Technology Acceptance Model (TAM) (Davis, 1993) is a well-established theory in information technology that focuses on an individual's intention to use a system. This intention is shaped by perceived usefulness (PU) and perceived ease of use (EOU). These determinants influence the individual's attitude, subsequently impacting behavioural intentions. Various studies, such as those by Gefen et al. (2003) and Jain et al. (2018), have applied these beliefs to predict purchasing intentions in the context of system and technology usage. TAM has been widely accepted and employed across diverse situations, including understanding potential consumers' attitudes on e-vendor websites (Venkatesh and Davis, 1996; Agarwal and Karahanna, 2000).

TAM, alongside other models, plays a significant role in explaining online transactions, emphasising the importance of hedonic features in technology and their impact on consumer intentions to transact online (Van der Heijden et al., 2001).

2.4.1 Perceived ease of use

Perceived ease of use, a determinant of the Technology Acceptance Model (TAM), is defined as the extent to which a user perceives the adoption of a particular technology to be hassle-free and easy (Davis et al., 1989; Hasni et al., 2021). In the context of online booking behaviour, perceived usefulness pertains to the extent to which an individual believes the website will enhance their information retrieval effectiveness. Similarly, perceived ease of use is defined as an individual's belief in the technology's capacity to streamline their tasks (Davis et al., 1989). They proposed that external factors, including technology-specific and system-specific factors, are influenced by perceived usefulness and perceived ease of use. According to Gao and Bai (2014), users are more inclined to use online services that they perceive as effortless and user-friendly. Thus,

H5. Perceived ease of use regarding hyper-personalisation using digital clienteling is positively related to online booking intention for a domestic vacation.

H6. Perceived ease of use regarding hyper-personalisation using digital clienteling is positively and indirectly related to online booking behaviour for a domestic vacation.

2.4.2 Perceived usefulness

Researchers have identified perceived usefulness (PU) as the extent to which a user believes that adopting a specific technology will improve their job performance (Davis et al., 1989; Hasni et al., 2021). It represents the extent to which an individual perceives an increase in effectiveness in obtaining information from a website. In the context of online shopping, TAM considers PU a significant determinant for predicting behavioural intentions. These perceptions influence consumers' attitudes and subsequently impact their intentions towards online booking. According to Gao and Bai (2014), perceived usefulness (PU) is related to the user's belief that utilising a specific online travel platform will enhance their performance in tour planning. This, in turn, increases consumer satisfaction and the likelihood of intending to use these technologies. Thus,

H7. Perceived usefulness regarding hyper-personalization using digital clienteling is positively related to online booking intention for a domestic vacation.

H8. Perceived usefulness regarding hyper-personalisation using digital clienteling is positively and indirectly related to online booking behaviour for a domestic vacation.

H9. Online booking intention towards hyper-personalisation using digital clienteling is positively related to online booking behaviour.

3. Methodology

The study adopts a quantitative approach and seeks to investigate how hyper-personalisation through digital clienteling influences online booking intention and behaviour for domestic vacations employing an integrated model (TAM/TRA).

3.1 Data Collection and Sampling Technique

This study explores domestic tourists' intention and behaviour towards hyper-personalisation through digital clienteling, specifically in the context of domestic vacation bookings. The research focuses on domestic tourists with a history of at least one online booking experience for a domestic vacation. Following Hair et al.'s (2014) guidance on SEM sample sizes, a total of 358 participants were surveyed, with 326 utilized for the analysis, meeting the recommended criteria for model complexity and measurement model characteristics.

Participants were randomly chosen through invitations to complete an online questionnaire shared across diverse Egyptian Facebook travel groups and pages during September and October 2023. Responses from individuals who hadn't engaged in online booking for a domestic vacation were excluded (an initial question was

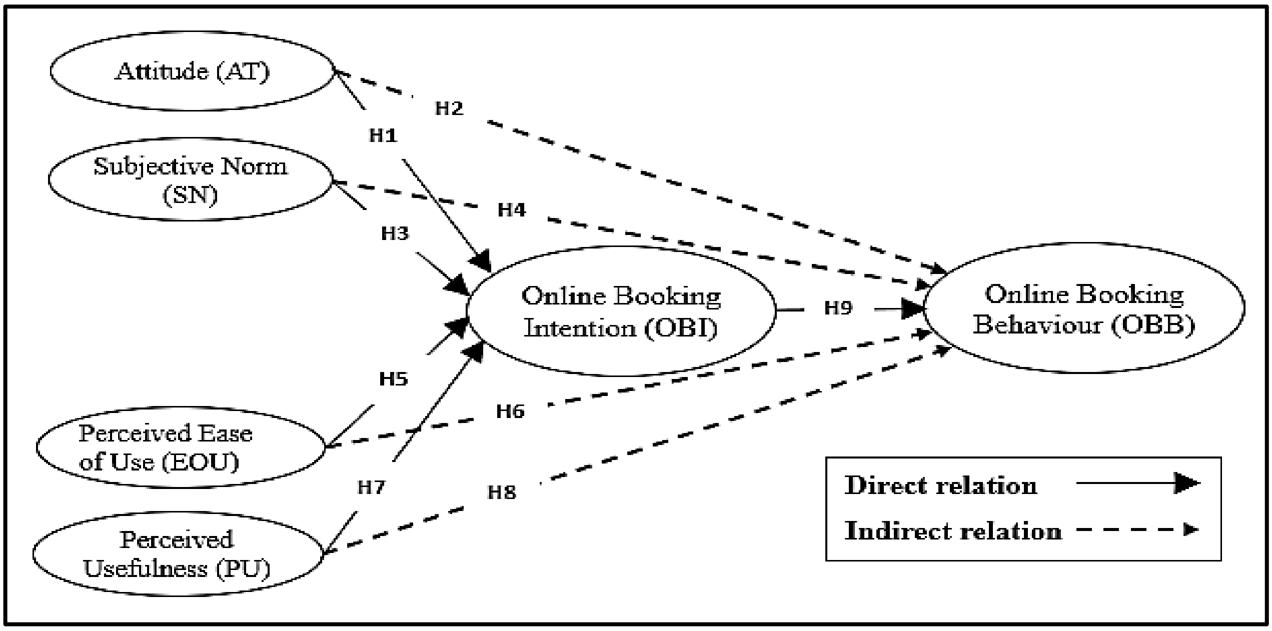

Fig. 1 - The Theoretical Model

2.5 Predicting Online Booking Behaviour Towards Hyper-Personalisation through Digital Clienteling

Building upon Jain et al. (2018), this study integrates the Theory of Reasoned Action (TRA) and the Technology Acceptance Model (TAM). The combined approach aims to comprehend intentions and predict booking behaviour during hyper-personalisation through digital clienteling. TRA and TAM posit that attitude, subjective norm, perceived ease of use, and perceived usefulness collectively influence online booking intentions, subsequently shaping online booking behaviour. Thus, embedded to limit the sample to only those who experienced online booking).

3.2 Study Measures:

The questionnaire has been crafted to assess the variables in accordance with the two theories, the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA). Questionnaire items and constructs utilised in the present study were adapted from various earlier research endeavours (e.g., Jain et al., 2021; Jain et al., 2018) (see Table 1).
In addition to the demographic questions, a total of 17 items have been included in the assessment. Each item was evaluated on a 7-point scale, where "1" signifies "strongly disagree" and "7" signifies "strongly agree." The questionnaire encompasses six constructs: attitude, subjective norms, perceived ease of use, perceived usefulness, online booking intention, and online booking behaviour.

3.3 Data analysis techniques

Using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, this quantitative research adopts a two-step approach, as recommended by Leguina (2015), examining the outer model for convergent and discriminant validity and subsequently assessing the inner model for hypothesis testing.

4. Findings and analysis

4.1 Descriptive Analysis

The survey participants comprised 69% males and 31% females, with a predominant representation of youth (approximately 42%) and young adults (around 30%), most of whom held a bachelor's degree (approximately 76%). Nearly half of the respondents (around 47%) participated in online booking for domestic vacations between 2 and 4 times. The majority

Table 1 – The Questionnaire Design Operationalization Analysis

Constructs	Items
Attitude (AT)	AT1: Online booking for a domestic vacation with a personalised feature is time-saving
	AT2: Online booking is available 24 hours a day, 7 days a week, which is pleasant
	AT3: Booking a personalised domestic vacation over the internet is a good idea
	AT4: I like to do online booking when I have personalised domestic vacation offerings
Subjective Norm (SN)	SN1: People who influence my behaviour would encourage me to use online booking for personalised domestic vacations
	SN2: People whose opinions I value would encourage me to use online booking for personalised domestic vacations
	SN3: People often seek my advice on selecting online offerings for domestic vacations
Perceived Ease of Use (EOU)	EOU1: Getting information specific to the domestic vacation from the personalised Web page would be easy
	EOU2: For me, getting domestic vacation information based on my requirements easily available from the website
Perceived Usefulness (PU)	PU1: A personalised Web page would be useful for getting information about domestic vacations and related services
	PU2: For me, valuable information about the domestic vacation is worthwhile
	PU3: Personalised information would enhance my effectiveness in getting useful domestic vacation information
Online Booking Intention (OBI)	OBI1: I intend to utilize the internet extensively for booking a personalised domestic vacation
	OBI2: I intend to use the internet booking in the future if personalised domestic vacations are provided
	OBI3: Given that I had access to the personalised internet booking, I predict that I would use it
Online Booking Behavior (OBB)	OBB1: I would feel comfortable booking personalised services over the internet on my own
	OBB2: The internet is a reliable way for me to take care of my personal affair

of participants fell into the middle- and high-income segments, as indicated in Table 2.

Table 2 – Respondents Demographic Profile

Demographic	Frequency	%	Demographic	Frequency	%
1. Gender			**4. Location:**		
- Male	225	69.02	- Cairo	69	21.17
- Female	101	30.98	- Giza	47	14.42
2. Age			- Alexandria	38	11.66
- Below 25	137	42.02	- Elgharbiya	34	10.43
- 26 - 35	97	29.75	- Kafr El-Sheikh	25	7.67
- 36 - 45	55	16.87	- Luxor	19	5.83
- 46 - 55	26	7.98	- Elsharqia	24	7.36
- 56 and above	11	3.37	- Port Said	21	6.44
3. Education:			- South Sinai	13	3.99
- No formal schooling	0	0.00	- Aswan	17	5.21
- High school graduate	66	20.25	- Red Sea	19	5.83
- Bachelor's degree	247	75.77			
- Master's degree	9	2.76			
- Doctorate degree	4	1.23			
5. Engagement in Online Booking for Domestic Vacations:			**6. Total Annual Income: (EGP)**		
- Once	72	22.09	- 0 - 50,000	4	1.23
- From 2 to 4 times	153	46.93	- 51,000 - 100,000	9	2.76
- From 5 to 7 times	74	22.70	- 101,000 -150,000	21	6.44
- More than 7 times	27	8.28	- 151,000 - 200,000	99	30.37
			- 200,000+	193	59.20
Total				**326**	**100%**

4.2 Evaluation of the Outer Measurement

4.2.1 Convergent validity (model's performance)

Various statistics were employed to evaluate the outer model's reliability and validity, and all items were retained. These statistics, including composite reliability (CR), Cronbach's alpha for internal consistency reliability, discriminant validity, and convergent validity, met the designated threshold values for loadings (≥0.6) (see Figure 2), Cronbach's α (≥0.7), CR (≥0.7), and average variance extracted (AVE) (≥0.5)

Table 3 – Evaluation of the Outer Measurement Model and VIF for Multicollinearity

Construct	Item	Outer loadings	Cronbach (above 0.70)	CR (above 0.70)	AVE (above 0.50)	Convergent validity CR > AVE AVE > 0.50	VIF
Attitude (AT) (VIF 1.674)	AT1	0.727	0.894	0.812	0.520	Yes	1.291
	AT2	0.674					1.292
	AT3	0.756					1.331
	AT4	0.724					1.271
Subjective Norm (SN) (VIF 1.868)	SN1	0.662	0.786	0.783	0.548	Yes	1.139
	SN2	0.778					1.236
	SN3	0.774					1.211
Perceived Ease of Use (EOU) (VIF 1.445)	EOU1	0.801	0.701	0.800	0.667	Yes	1.124
	EOU2	0.832					1.125
Perceived Usefulness (PU) (VIF 1.869)	PU1	0.768	0.817	0.797	0.566	Yes	1.249
	PU2	0.756					1.218
	PU3	0.733					1.203
Online Booking Intention (OBI) (VIF 1.000)	OBI1	0.797	0.873	0.821	0.605	Yes	1.384
	OBI2	0.749					1.253
	OBI3	0.786					1.322
Online Booking Behavior (OBB)	OBB1	0.809	0.778	0.793	0.657	Yes	1.109
	OBB2	0.812					1.107

(Hair et al., 2021; Gamiljj and Abd Rahman, 2023). This indicates meeting the criteria for the convergent validity of the model. (see Table 3).

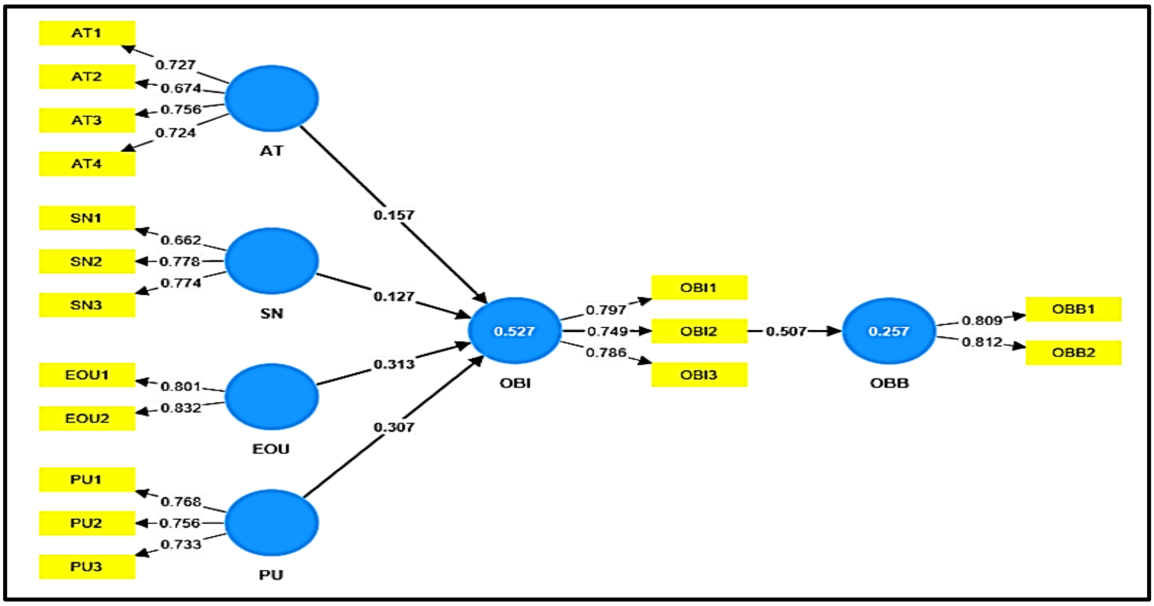

Fig. 2 – Factor Loading Results (Smart-PLS Output)

4.2.2 Discriminant Validity

The Fornell and Larcker criterion was used to ensure discriminant validity, comparing the square root of AVE with latent variable correlations. The criterion's results indicate that the diagonal bold values consistently exceed those preceding them horizontally, demonstrating discriminant validity for each construct. The loading on each construct is consistently higher than all cross-loadings with other constructs, confirming the criterion's requirements (Hair et al., 2021; Gamiljj and Abd Rahman, 2023). (see Table 4).

predictions with data, indicating the extent of variation in dependent variables explained by predictor variables (Hair et al., 2021). An R2 value of 0.10 is considered satisfactory, while an R2 of 0.5 suggests a moderate correlation (Gamiljj and Abd Rahman, 2023). The calculated R2 in this study for online booking intention (OBI) is 0.527, indicating an effective prediction of the dependent variable (OBI) by the independent variables (attitude (AT), subjective norms (SN), perceived usefulness (PU), and perceived ease of use (EOU)). The calculated R2 for online booking behaviour (OBB) is 0.257, indicating an effective prediction of the dependent variable (OBB) by the independent variables (AT, SN, EOU, and PU). All of which confirm a satisfactory and good fit for the model.

Table 4 - Discriminant Validity - Fronell-Larcker Criterion

	AT	EOU	OBB	OBI	PU	SN
Attitude (AT)	**0.721**					
Perceived Ease of Use (EOU)	0.410	**0.817**				
Online Booking Behavior (OBB)	0.386	0.472	**0.810**			
Online Booking Intention (OBI)	0.519	0.592	0.507	**0.778**		
Perceived Usefulness (PU)	0.517	0.526	0.426	0.628	**0.753**	
Subjective Norms (SN)	0.589	0.418	0.407	0.532	0.593	**0.740**

4.3 Assessment of the Structural Inner Model

4.3.1 Coefficient of determination (R2) and model fit

In PLS-SEM, the coefficient of determination (R2) assesses the alignment of regression

4.3.2 Hypotheses testing

Hypothesis testing evaluates the proposed connection between constructs, where the independent variables (IV) significantly influence the dependent variables (DV). A relationship is deemed significant if the T-value surpasses 1.96 or the P-value is below 0.05 (Hair et al., 2021). To ensure result stability, bootstrapping is performed in smart PLS4 with 5000 subsamples (Gamiljj and Abd Rahman, 2023).

Table 5 - Hypothesis Testing (Bootstrapping)

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1. AT -> OBI	0.157	0.161	0.059	2.67	0.008	Supported
H2. AT -> OBI -> OBB	0.080	0.082	0.031	2.604	0.009	Supported
H3. SN -> OBI	0.127	0.128	0.061	2.078	0.038	Supported
H4. SN -> OBI -> OBB	0.064	0.066	0.033	1.950	0.051	Not supported
H5. EOU -> OBI	0.313	0.309	0.056	5.583	0.000	Supported
H6. EOU -> OBI -> OBB	0.159	0.157	0.035	4.594	0.000	Supported
H7. PU -> OBI	0.307	0.307	0.057	5.434	0.000	Supported
H8. PU -> OBI -> OBB	0.156	0.156	0.032	4.796	0.000	Supported
H9. OBI -> OBB	0.507	0.508	0.050	10.073	0.000	Supported

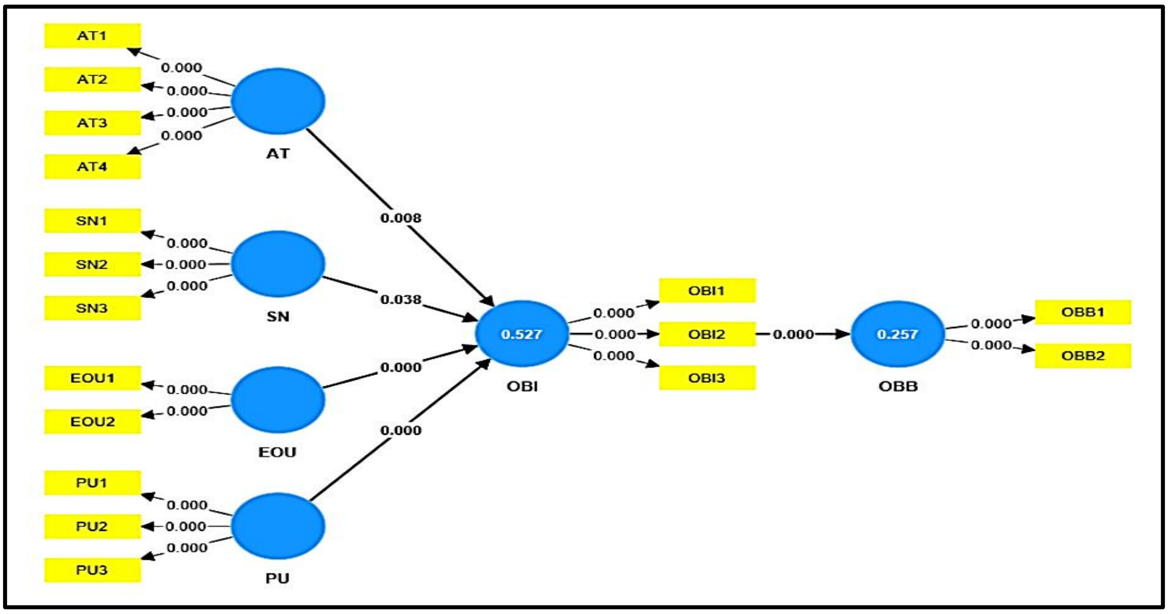

Fig. 3 – Bootstrapping (P values: Smart-PLS Output)

As shown in Table 5, eight out of nine hypotheses in the predetermined path model are statistically significant, meeting the criteria of a T-value greater than 1.96 and a P-value less than 0.05. As a result, hypotheses H1, H2, H3, H5, H6, H7, H8, and H9 received support, whereas hypothesis H4 (β = -0.064, t-value = 1.95, p = 0.051) did not receive support.

5. Discussion and Implications

The calculated R2 values for online booking intention (OBI) and online booking behaviour (OBB) were 0.527 and 0.257, respectively. These values indicate a satisfactory and good fit for the model (see Section 4.3.1), demonstrating that the proposed model effectively explains the variance in online booking intention and behavior. The alignment of regression predictions with data suggests that the integrated TAM/TRA model is well-suited to predict tourists' online booking decisions.

The study's demographic analysis revealed a predominant representation of male participants (69%) (see Table 2), primarily consisting of youth and young adults holding a bachelor's degree. This demographic profile suggests that digital clienteling for domestic vacations appeals more to a younger and more educated audience, aligning with previous studies highlighting the role of technology adoption among the youth (Pinto and Castro, 2019; Elsawy, 2023) and the significance of education in influencing digital behaviour (Elsawy, 2023).

Eight out of nine hypotheses received support (see Table 5), indicating a significant relationship between constructs. The positive relationships between attitude, subjective norms, perceived ease of use, perceived usefulness, and online booking intention and behaviour align with various theoretical and empirical studies (e.g., Fokides, 2017; Gao and Bai, 2014; Hefny, 2021; Jain et al., 2021; Jain et al., 2018; Ulker-Demirel and Ciftci, 2020). According to Koo and Lee (2018), behaviour is directly influenced by attitudes (AT) and subjective norms (SN) through the mediation of behavioural intention. The Hefny (2021) study confirmed a positive impact of the two primary variables in the TAM model (EOU and PU) on the intention to purchase airline tickets online. However, hypothesis H4 did not achieve statistical significance ($\beta = -0.064$, t-value = 1.95, $p = 0.051$), suggesting that subjective norms might not have an indirect impact on online booking behaviour for domestic tourists in Egypt, contrary to initial expectations.

5.1 Practical Implications

According to Jain et al. (2021), digital transformations result in innovations and financial gains for businesses. Thus, in order to gain benefits, businesses must pay more attention and make more efforts, especially since Elsawy (2023) concluded that, although the idea of e-business has been embraced, only a limited number of travel agencies in Egypt incorporate it into their day-to-day activities. Moreover, Elsawy (2023) stressed the need for decision-makers in Egypt to prioritise ICT skills in educational curricula. This ensures that graduates are well-prepared to understand and utilise technology in the marketplace.

This study holds substantial value for the tourism industry by providing actionable insights into the behaviour of domestic tourists in the context of hyper-personalised digital clienteling. The practical implications offer tourism businesses a roadmap for formulating effective marketing strategies and optimising digital platforms, ultimately enhancing customer engagement and satisfaction.

H1 and H2: Attitude towards hyper-personalisation:

A positive attitude towards hyper-personalisation significantly influences domestic tourists' online booking intentions. Moreover, this positive attitude indirectly contributes to their online booking behaviour. Tourism businesses should focus on cultivating favourable perceptions of hyper-personalisation to enhance online booking engagement.

H3: Subjective norms regarding hyper-personalisation:

The study underscores the importance of subjective norms in shaping domestic tourists' online booking intentions. Businesses should consider social influences and incorporate strategies that align with the preferences and recommendations of individuals within tourists' social circles.

H5 and H6: Perceived ease of use regarding hyper-personalisation:

Domestic tourists' perception of the ease of using digital clienteling for hyper-personalisation significantly impacts their online booking intentions. Simplifying the user experience and ensuring a user-friendly interface can contribute to increased online booking engagement.

H7 and H8: Perceived usefulness regarding hyper-personalisation:

The perceived usefulness of hyper-personalisation through digital clienteling positively influences domestic tourists' online booking intentions. Tourism businesses should highlight the practical benefits of personalised services to enhance tourists' perceptions of their usefulness and encourage online booking. According to Jain et al. (2018), implementing personalised recommendations and efficient booking processes can enhance the overall user experience and positively impact booking intentions and behaviours.

Moreover, the study suggests that marketing efforts should target a younger, educated demographic, emphasizing the benefits of hyper-personalised digital clienteling for domestic vacations. Consistent with the results of the study, Aref and Okasha (2020) demonstrated that younger Egyptians exhibit a favourable inclination towards online shopping in contrast to preceding generations.

5.2 Theoretical Implications

The theoretical integration of TAM and TRA contributes to the advancement of technology adoption models. It provides a holistic understanding of tourists' decision-making processes in the context of hyper-personalized digital clienteling. This contributes to the theoretical foundation of technology adoption and behavioral intentions in the tourism industry.

The study's focus on hyper-personalised digital clienteling in the domain of domestic tourism represents a novel contribution to the existing literature. While digital transformations and hyper-personalization have been explored in various industries, the study uniquely addresses the specific nuances of tourists' online booking behaviour for domestic vacations, particularly in developing countries like Egypt.

The study's focus on the Egyptian context and its domestic tourism market adds originality by exploring a region that is underrepresented in the existing literature. The findings provide insights into the specific factors influencing online booking intentions and behaviours in a developing country, offering a valuable contribution to the global understanding of technology adoption in diverse cultural settings.

6. Conclusions

This study sheds light on the dynamics of hyper-personalized digital clienteling in the context of domestic tourism. The integration of TAM and TRA proved effective in explaining tourists' online booking intentions and behavior. This study not only provides practical insights for marketers and businesses in the tourism industry but also contributes to the theoretical understanding of technology adoption in the context of hyper-personalized digital clienteling. By emphasizing the demographic targeting of marketing efforts and optimizing digital platforms for user-friendliness, businesses can enhance the effectiveness of their online booking services. The integration of TAM and TRA offers a comprehensive framework for researchers to explore the complex interplay between technology acceptance, behavioral intentions, and actual behavior in the evolving landscape of the tourism industry.

6.1 Limitations and Future Research Directions

The study focused on Egyptian domestic tourists, limiting the generalizability of findings. Future research should explore diverse cultural contexts to validate the model's applicability. Moreover, the non-significant relationship between subjective norms and online booking behavior challenges traditional TRA expectations. This calls for further exploration into the nuanced factors influencing subjective norms in the context of digital clienteling for domestic vacations. Further research could delve into the specific factors influencing subjective norms in online booking behavior to unravel the complexities surrounding social influences. Furthermore, conducting longitudinal studies could provide insights into the evolving nature of tourists' attitudes and behaviors towards hyper-personalised digital clienteling over time.

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