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The Moderating Role of Digital Service Quality in the Relationship Between Digital Transformation, the Internet of Things, Artificial Intelligence, and Customer Satisfaction in Marketing Companies in Saudi Arabia

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Abstract

This study investigates the impact of Digital Transformation (DT), Artificial Intelligence (AI), the Internet of Things (IoT), and Digital Service Quality (DSQ) on Customer Satisfaction (CS) in marketing companies in Saudi Arabia, and examines whether DSQ moderates these relationships. Drawing on six complementary frameworks — including Dynamic Capabilities Theory, the Technology Acceptance Model (TAM), and the Information Systems Success Model — the study analyses data from a purposive sample of 269 respondents using PLS-SEM in SmartPLS 4. AI, IoT, and DSQ each exert a significant positive direct effect on CS, with AI the strongest driver ($f^2 = 0.202$), followed by DSQ ($f^2 = 0.123$) and IoT ($f^2 = 0.120$). DT was not statistically significant ($f^2 = 0.009$), suggesting that organisational-level transformation has not yet translated into customer-perceived outcomes in this context. DSQ does not significantly moderate the technology–CS relationships, indicating that technological benefits operate independently of perceived service quality. These null moderation findings are reinterpreted through the IS Success Model as evidence that technological value and service quality act as parallel, additive satisfaction drivers rather than interactive ones. The study contributes theoretically by integrating multiple frameworks into a unified model, offers practical guidance for marketing firms, and aligns with the United Nations Sustainable Development Goals by showing how these technologies support SDG 8 (decent work and economic growth) and SDG 9 (industry, innovation, and infrastructure), and enable the more responsible consumption patterns envisaged in SDG 12. Limitations include non-probability sampling and a single-sector focus in Riyadh.

1. Introduction

The accelerated advancement of digital technologies has profoundly transformed industries, societies, and economies worldwide. The World Economic Forum (2023) estimates that digital transformation (DT) could contribute up to USD 100 trillion to the global economy by 2025 by allowing organisations to enhance operational efficiency, develop innovative products and services, and improve customer satisfaction (CS). DT can be defined as the comprehensive integration of digital technologies into all business functions, leading to fundamental changes in how organisations operate and create value for customers (Kraus et al., 2021; Kraus et al., 2022; Robertsone & Lapina, 2023). This transformation involves the adoption of advanced technologies such as artificial intelligence (AI), big data analytics, cloud computing, and the Internet of Things (IoT), which support process optimisation, more informed decision-making, and continuous innovation. Core elements of DT include strategic orientation, technological implementation, and organisational culture change (Butt et al., 2024; Kao et al., 2024; Costa, 2024). Nevertheless, this technological era also poses substantial challenges, as firms must adapt to rapid change, shifting customer expectations, and increasing competitive pressure.

Within the business context, DT, AI, and IoT are widely recognised as critical drivers of long-term performance and sustainability. Evidence from Tarigan et al. (2025) indicates that organisations embracing digital technologies are 23% more likely to outperform competitors in terms of profitability. Digital initiatives also strongly influence CS, which represents a vital source of competitive advantage. By utilising data analytics, AI, cloud platforms, and IoT solutions, companies can deliver integrated and highly personalised customer experiences. Despite these advantages, prior research points to a disconnect between the expected and realised outcomes of DT, AI, and IoT, as many organisations experience only modest improvements in key performance indicators (Guo & Xu, 2021). Consequently, firms often struggle to implement digital strategies that simultaneously enhance organisational performance and CS.

CS reflects the extent to which products and services meet or exceed customer expectations. It is shaped by factors such as product quality, service quality, pricing, and the overall customer experience. DT has significantly enhanced CS by facilitating service personalisation, improving access, and strengthening interactive communication channels (Matarazzo et al., 2021; Pascucci et al., 2023; Latupeirissa et al., 2024). Moreover, perceived usefulness, ease of use, and price perceptions have been shown to positively affect CS and, in turn, customer loyalty (Suryatenggara & Dahlan, 2022).

Despite growing interest in this area, empirical studies examining the joint effects of DT, AI, and IoT on both organisational performance and CS remain scarce. Kretschmer and Khashabi (2020) proposed an integrated framework for DT and organisation design but focused primarily on structural change without empirically linking it to CS. Similarly, studies by Müller et al. (2024) and Leso et al. (2023) emphasise leadership and organisational culture as drivers of digital excellence, yet they overlook CS outcomes. Research by Rizvanović et al. (2023) addresses customer-oriented digital marketing strategies but does not provide a

comprehensive assessment of overall firm performance. Given these gaps, this study examines the impact of DT, AI, IoT, and DSQ on CS in the context of rapid technological change, and introduces DSQ as a potential moderator of the technology–satisfaction relationships. A secondary aim is to clarify how the deployment of these digital technologies in marketing firms generates not only customer value but also sustainable development outcomes, thereby contributing evidence relevant to the United Nations Sustainable Development Goals agenda in emerging economies. The Saudi context is particularly timely: under Vision 2030, the Kingdom is actively pursuing digital economic diversification, with AI spending projected to reach $1.9 billion by 2027 and the IoT market estimated to reach $2.9 billion by 2025 (Alateeg et al., 2024; Al-Ayed et al., 2023). Despite this policy momentum, empirical evidence on how digital technologies jointly influence CS in Saudi marketing companies remains limited (Alotaibi, 2024).

Beyond its managerial relevance, this study speaks directly to the sustainable development agenda. The effective integration of AI, IoT, and high-quality digital services in marketing companies contributes to several United Nations Sustainable Development Goals (SDGs). Digital technologies that raise productivity, create new skilled roles, and enable inclusive economic participation advance SDG 8 (Decent Work and Economic Growth), while AI and IoT represent foundational technologies underpinning the innovation and infrastructure agenda captured by SDG 9 (Industry, Innovation, and Infrastructure). High-quality digital services that reduce informational waste, enhance resource allocation, and enable customers to make more informed choices likewise support the responsible consumption patterns envisaged in SDG 12 (Responsible Consumption and Production). Saudi Arabia's Vision 2030 reform programme is explicitly aligned with these Goals, making the Saudi marketing sector a particularly relevant context in which to examine how digital transformation delivers both customer value and sustainable economic and social outcomes.

2. Theoretical Foundation

This study draws on six complementary theoretical frameworks. Together, they provide the conceptual architecture through which the relationships among DT, AI, IoT, DSQ, and CS are explained, and they supply the logical basis for each hypothesis developed in Section 3.

2.1 Dynamic Capabilities Theory

Teece, Pisano, and Shuen (1997) define dynamic capabilities as an organisation's ability to sense environmental change, seize emerging opportunities, and reconfigure its resource base to sustain competitive advantage. In digital business contexts, this framework explains how firms develop technology-enabled capabilities that allow them to continuously innovate, adapt, and create customer value (Saeedikiya et al., 2024; de Miguel et al., 2022). This theory provides the overarching framework for the study: DT, AI, and IoT represent distinct technological capabilities that organisations deploy to sense and respond to customer needs. H1 (DT→CS), H2 (IoT→CS), and H3 (AI→CS) all flow from this premise — firms that effectively deploy digital technologies as dynamic capabilities generate superior customer experiences and satisfaction.

2.2 Technology Acceptance Model (TAM)

Davis (1989) proposed the Technology Acceptance Model (TAM) to explain how users form intentions to adopt technology based on two core beliefs: perceived usefulness and perceived ease of use. TAM has since been extended into the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), broadening the antecedents of technology adoption. Both frameworks have been extensively applied to consumer adoption of digital services, mobile applications, and smart devices (Singh et al., 2020; Alkis & Kose, 2022; Al-Hattami et al., 2026). In this study, TAM provides the individual-level mechanism through which IoT (H2) and AI (H3) influence CS: consumers evaluate whether IoT connectivity and AI-driven personalisation are useful and easy to interact with, and those perceptions directly shape satisfaction. When customers find AI recommendations accurate and IoT services seamlessly integrated into their lives, they report higher CS levels. TAM also underpins H4 (DSQ→CS): the efficiency and reliability dimensions of DSQ map directly onto TAM's ease-of-use and usefulness constructs.

2.3 Expectation-Confirmation Theory (ECT)

Oliver (1980) proposed Expectation-Confirmation Theory (ECT) to explain how satisfaction emerges from the comparison between pre-consumption expectations and post-consumption performance perceptions. When actual service performance confirms or exceeds expectations, satisfaction results; when performance falls short, dissatisfaction ensues. ECT provides the psychological mechanism through which all four independent variables (DT, IoT, AI, DSQ) translate into CS (H1–H4): each technology raises customer expectations for service efficiency, personalisation, and responsiveness, and CS arises when those expectations are confirmed. ECT also explains why DT's effect on CS may be weaker than AI's or IoT's — DT operates primarily at the organisational infrastructure level, while customers confirm expectations primarily through direct service interactions.

2.4 Service Quality Theory (SERVQUAL)

Parasuraman, Zeithaml, and Berry (1988) developed the SERVQUAL framework to measure service quality across five dimensions: tangibles, reliability, responsiveness, assurance, and empathy. In digital environments, these dimensions have been adapted into DSQ frameworks assessing website efficiency, information accuracy, privacy protection, and responsiveness (Parasuraman et al., 2005; Raza et al., 2020; Kim & Jeon, 2025). SERVQUAL grounds H4 (DSQ→CS): customers evaluate digital platforms against these service quality dimensions, and those evaluations translate directly into satisfaction. The moderation hypotheses (H5, H6, H7) also draw on SERVQUAL by proposing that service quality perceptions amplify or attenuate the satisfaction effects of digital technologies. The rejection of H5–H7 suggests that in digitally intensive environments, the evaluative processes associated with technological value and service quality quality operate through separate cognitive pathways.

2.5 Information Systems Success Model

DeLone and McLean (1993, 2003) proposed that system quality, information quality, and service quality are direct antecedents of user satisfaction and net benefits. In digital marketing contexts, this model explains why DSQ is a direct and significant predictor of CS (H4). Critically, the IS Success Model also provides a theoretical reinterpretation of the null moderation findings (H5–H7): the model's architecture suggests that system quality and user satisfaction are related through direct additive effects rather than interactive ones, meaning that the quality of the digital interface independently predicts satisfaction without necessarily amplifying the effects of underlying technologies. This offers a theoretically grounded explanation for why DSQ and DT, IoT, and AI may each drive CS without their effects being contingent upon one another.

2.6 Stimulus-Organism-Response (SOR) Framework

Mehrabian and Russell (1974) proposed the SOR framework to explain how environmental stimuli (S) trigger internal cognitive and affective states in the organism (O), which in turn drive behavioural responses (R). Applied to digital marketing, technology characteristics and service features serve as stimuli that shape customer perceptions and evaluations (organism), culminating in behavioural outcomes such as satisfaction and loyalty (response) (Yan et al., 2020). The overall structure of this study's model follows SOR logic: DT, IoT, AI, and DSQ are stimuli that shape customer cognitive-affective states, producing satisfaction as the response. DSQ's proposed moderating role (H5–H7) is grounded in SOR: as a stimulus modifier, DSQ was theorised to amplify or attenuate the satisfaction responses triggered by other technological stimuli.

2.7 Digital Technologies and Sustainable Development

Beyond the cognitive and organisational mechanisms articulated in the preceding frameworks, a growing body of work links DT, AI, IoT, and DSQ to the United Nations 2030 Agenda for Sustainable Development. Digital technologies contribute to SDG 8 (Decent Work and Economic Growth) by raising productivity, creating higher-skilled digital employment, and broadening economic participation through digitally delivered services. They also underpin SDG 9 (Industry, Innovation, and Infrastructure) as the core innovation infrastructure on which contemporary industries rely, with AI and IoT serving as foundational general-purpose technologies for digitalised economies. High-quality digital service platforms — the focus of the DSQ construct in this study — additionally support SDG 12 (Responsible Consumption and Production) by reducing informational asymmetries, improving resource matching, and enabling customers to make more sustainable consumption choices through transparent, reliable, and personalised service experiences. Within the Saudi Arabian setting, these linkages are explicit in the Vision 2030 reform programme, which positions digital transformation as a lever for simultaneously achieving economic diversification, innovation capacity, and sustainable consumption patterns (Alateeg et al., 2024; Al-Ayed et al., 2023). Recent empirical work further confirms that digital service quality dimensions shape customer satisfaction and loyalty in ways that directly bear on sustainable

business practices under environmental uncertainty (Kim & Jeon, 2025). Together, this evidence indicates that the technological and customer-satisfaction outcomes investigated in the present study are inseparable from their sustainable development implications and provides an additional rationale for the integrative model adopted here.

2.8 Theoretical Synthesis

These six frameworks work in concert. The SOR framework provides the overall structural logic. Dynamic Capabilities Theory explains the organisational-level mechanisms through which DT, AI, and IoT create customer value. TAM explains the individual-level cognitive processes through which customers evaluate and respond to these technologies. ECT provides the psychological mechanism through which technology experiences translate into satisfaction judgements. SERVQUAL and the IS Success Model ground the DSQ construct and explain its direct and non-moderating effects. Together, they predict: (1) each digital technology independently drives CS (H1–H4); (2) DSQ theoretically moderates technology–satisfaction relationships (H5–H7); and (3) the empirical rejection of H5–H7 can be reinterpreted through the IS Success Model as evidence that technological capability and service quality are parallel, additive satisfaction drivers rather than multiplicatively interactive ones — a finding that advances theoretical understanding rather than simply reporting failure.

3. Theoretical Framework and Hypothesis Development

3.1 Digital Transformation and Customer Satisfaction (H1)

DT represents the comprehensive integration of digital technologies into all organisational functions, enabling firms to reinvent business processes, enhance customer interactions, and create new value propositions (Kraus et al., 2021; Blanka et al., 2022). Organisations leveraging DT can identify opportunities, mitigate threats, and sustain competitiveness, all of which contribute to enhanced CS (Liu & He, 2024). Digital innovations significantly accelerate the evolution of traditional business models and enable new service development (Jiang, 2024), while customer-centric DT initiatives — focused on improving product quality and communication channels — consistently improve CS outcomes (Cai et al., 2024; Cheng et al., 2023). Notably, Al-Hattami et al. (2025) demonstrate through a moderated mediation design that digital accounting systems positively influence marketing performance in SMEs, confirming that the translation of digital investments into customer-facing outcomes is contingent on organisational context and implementation quality. Based on Dynamic Capabilities Theory, ECT, and the foregoing empirical evidence, the following hypothesis is proposed:

H1: Digital Transformation (DT) has a positive and significant direct impact on Customer Satisfaction (CS) in marketing companies in Saudi Arabia.

3.2 Internet of Things and Customer Satisfaction (H2)

IoT enables interconnected communication among devices and has emerged as a fundamental driver of contemporary innovation, with applications spanning smart transportation, urban development, supply chain management, and modern marketing (Brous et al., 2020; Lee & Lee, 2018). IoT technologies provide substantial advantages related to consumption efficiency and enhanced CS by enabling real-time monitoring, data-driven personalisation, and improved service responsiveness (Eslami et al., 2024; Ren et al., 2024). Adopting a consumer-oriented approach, IoT positively affects technology acceptance and adoption behaviour (Shahzad et al., 2024), with consumers evaluating whether potential benefits outweigh privacy, risk, and trust concerns (Goad et al., 2021; Lim & Rasul, 2022; Taneja & Ali, 2021). Grounded in TAM and Dynamic Capabilities Theory, the following hypothesis is proposed:

H2: The Internet of Things (IoT) has a positive and significant direct impact on Customer Satisfaction (CS) in marketing companies in Saudi Arabia.

3.3 Artificial Intelligence and Customer Satisfaction (H3)

AI has become a transformative force in sales and marketing, reshaping how organisations engage with customers (Luo et al., 2021; Singh et al., 2020). By leveraging large-scale datasets, AI systems customise interactions and recommendations according to individual preferences and behaviours (Rafieian & Yoganarasimhan, 2023), enabling dynamic pricing models, AI-powered

chatbots, virtual assistants, and predictive CRM systems (Ledro et al., 2022; Paschen et al., 2020). This heightened personalisation fosters feelings of recognition and appreciation, significantly improving CS and loyalty (Rane, 2023). AI's ability to analyse customer feedback in real time and continuously improve service quality reinforces its role as a critical CS driver (Gao et al., 2022; Ameen et al., 2021). Based on TAM, ECT, and Dynamic Capabilities Theory, the following hypothesis is proposed:

H3: Artificial Intelligence (AI) has a positive and significant direct impact on Customer Satisfaction (CS) in marketing companies in Saudi Arabia.

3.4 Digital Service Quality, Customer Satisfaction, and Moderation (H4–H7)

DSQ is broadly defined as customers' overall assessment of the effectiveness and excellence of services provided in the digital marketplace (Nagar & Ghai, 2020). It has been operationalised through dimensions including efficiency, reliability, responsiveness, privacy, and communication (Parasuraman et al., 2005; Raza et al., 2020). Recent empirical evidence confirms that digital service quality dimensions — particularly system quality, information quality, and service quality — significantly predict customer satisfaction and brand loyalty in banking and marketing contexts (Kim & Jeon, 2025). Factors such as attentiveness, responsiveness, friendliness, and accessibility are key drivers of CS (Singh et al., 2020), while trust and consumer uncertainty play important roles in shaping online CS outcomes (Gupta & Bhatt, 2021). High DSQ reduces uncertainty in digital interactions and enhances trust, ease of use, and perceived value, all of which translate into greater CS. Grounded in SERVQUAL, the IS Success Model, and TAM, the following direct effect hypothesis is proposed:

H4: Digital Service Quality (DSQ) has a positive and significant direct impact on Customer Satisfaction (CS) in marketing companies in Saudi Arabia.

Beyond its direct effect, DSQ is theorised to moderate the relationships between DT, IoT, AI, and CS. Drawing on the SOR framework, DSQ functions as a stimulus modifier: superior digital service environments may amplify the positive effects of advanced technologies on CS by enhancing the overall customer experience, reducing friction, and strengthening trust. Conversely, poor DSQ may attenuate these effects by introducing uncertainty and dissatisfaction that overwhelm technological benefits. Based on these arguments, the following moderation hypotheses are proposed:

H5: DSQ moderates the relationship between DT and CS, such that higher DSQ strengthens the positive effect of DT on CS.

H6: DSQ moderates the relationship between IoT and CS, such that higher DSQ strengthens the positive effect of IoT on CS.

H7: DSQ moderates the relationship between AI and CS, such that higher DSQ strengthens the positive effect of AI on CS.

4. Methodology

4.1 Data and Sample

The study targeted marketing and manufacturing firms in Saudi Arabia that rely on digital platforms in their marketing practices, including AI, DT, IoT, and DSQ. A purposive non-probability sampling approach was adopted to ensure inclusion of respondents relevant to the study's aims (Shinya et al., 2023). Data were gathered through structured questionnaires administered electronically via Google Forms, with 305 participants initially invited. Of the distributed questionnaires, 282 were returned, and after screening for missing data and confirming data normality, 269 responses were retained for analysis (Wah & Ng, 2024). This sample size satisfies established SEM guidelines recommending a minimum of 250 observations (Gaskin et al., 2025).

Non-probability purposive sampling was selected to closely align the sample with the research objectives. The study acknowledges the inherent limitations of this approach, particularly the risk of overrepresenting respondents with higher levels of technical expertise, which may restrict the generalisability of results across populations with differing degrees of digital proficiency (Reedy et al., 2023). Future research is encouraged to employ probability-based sampling to enhance representativeness. Additionally, variations in respondents' comprehension of advanced concepts such as AI, DT, and IoT may have affected responses.

4.2 Questionnaire and Data Collection

Data were collected using revised questionnaires administered to marketing and production companies in Saudi Arabia. Responses were measured on a five-point Likert scale, ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). The questionnaire comprised 20 items across five constructs (DT, IoT, AI, DSQ, CS), with four items per construct. Data collection was conducted over a two-month period from September to October 2024. Given the characteristics of the target sample, the survey was distributed electronically via Google Forms, with links shared through email and WhatsApp groups.

4.3 Analytical Approach

SmartPLS 4 (Cheah et al., 2024) was utilised to assess both the measurement and structural models (Sarstedt et al., 2024). Partial Least Squares Structural Equation Modelling (PLS-SEM) was selected due to its effectiveness in analysing complex research frameworks, handling multivariate datasets, and examining moderation effects (Magno et al., 2024; Hair & Alamer, 2022). The analysis followed a two-step procedure: the measurement model was first evaluated for validity and reliability (Dos Santos & Cirillo, 2023), followed by structural model analysis to test the proposed hypotheses (Cheung et al., 2024).

Principal component analysis (PCA) was conducted to assess construct unidimensionality (Baharum et al., 2023), and confirmatory factor analysis (CFA) verified that the 20 observed indicators adequately represented the five latent variables (Sureshchandar, 2023). Internal consistency reliability was assessed using Cronbach’s alpha, with values above 0.7 considered acceptable (Malkewitz et al., 2023). Discriminant validity was examined using the HTMT criterion (Dirgiatmo, 2023) and the Fornell–Larcker criterion (Hair et al., 2022).

4.4 Common Method Bias

Because all constructs were collected from the same respondents at a single point in time via a single online survey, common method bias (CMB) represents a potential threat to validity. Harman’s single-factor test was conducted as a procedural remedy. The results showed that the first unrotated factor accounted for less than 50% of the total variance, providing initial evidence that CMB does not pose a serious threat to the study’s conclusions. Future research should consider multi-source data collection or marker variable approaches to further address this concern (Carrion-Bosquez et al., 2025).

5. Results

5.1 Measurement Model

Table 1 reports the EFA and CFA results. All factor loadings exceed 0.80, confirming indicator reliability. All constructs achieved Cronbach’s alpha values above 0.85, indicating high internal consistency.

Table 1
Measurement Model: EFA, CFA, Reliability, and Validity

Construct	Item	Factor Loading	Outer Weights	VIF	PCA %	Cronbach's α	t-value	p-value	CR (rho_a)	CR (rho_c)	AVE
AI	AI1	0.852	0.279	2.263	76.574	0.864	44.385	0.000	0.865	0.907	0.709
	AI2	0.859	0.279	2.386			41.389	0.000			
	AI3	0.850	0.300	2.171			47.046	0.000			
	AI4	0.807	0.331	1.650			33.596	0.000			
CS	CS1	0.871	0.305	3.043	76.803	0.884	50.397	0.000	0.886	0.920	0.743
	CS2	0.909	0.293	3.936			73.336	0.000			
	CS3	0.878	0.286	2.684			62.338	0.000			
	CS4	0.786	0.275	1.803			26.902	0.000			
DSQ	DSQ1	0.873	0.291	2.473	76.668	0.889	52.850	0.000	0.889	0.923	0.751
	DSQ2	0.889	0.284	3.261			61.723	0.000			
	DSQ3	0.884	0.281	3.032			56.501	0.000			
	DSQ4	0.820	0.300	1.875			31.668	0.000			
DT	DT1	0.888	0.287	3.503	76.487	0.905	65.953	0.000	0.906	0.934	0.779
	DT2	0.896	0.283	3.802			68.514	0.000			
	DT3	0.886	0.275	3.107			51.965	0.000			
	DT4	0.859	0.288	2.643			43.981	0.000			
IoT	IoT1	0.826	0.304	2.039	75.946	0.855	38.551	0.000	0.857	0.902	0.697
	IoT2	0.808	0.280	1.991			30.511	0.000			
	IoT3	0.864	0.317	2.644			45.581	0.000			
	IoT4	0.842	0.295	2.503			35.123	0.000			

Note. Factor loadings (EFA) and t-values (CFA) are identical — the duplicate CFA loading column has been removed. Construct-level statistics (PCA %, Cronbach's α, CR, AVE) appear on the first item row of each construct. All factor loadings > 0.80; all Cronbach's α > 0.85; all CR (rho_c) > 0.90; all AVE > 0.69, satisfying convergent validity thresholds. DT = Digital Transformation; IoT = Internet of Things; AI = Artificial Intelligence; DSQ = Digital Service Quality; CS = Customer Satisfaction.

Table 2 presents HTMT ratios for discriminant validity. While most values fall within acceptable ranges, several ratios between closely related constructs — particularly DT and AI (0.892), IoT and DT (0.883), and IoT and AI (0.871) — approach the conservative 0.85 threshold. All interaction term pairs also show HTMT values above 0.85. These elevated values suggest that although the constructs are theoretically distinct, their empirical boundaries partially overlap within the marketing context of this sample. This is acknowledged as a study limitation and should motivate future research to develop more discriminant measurement instruments.

Table 2
Discriminant Validity — HTMT Ratios

AI	AI	CS	DSQ	DT	IoT	DSQ×DT	DSQ×IoT	DSQ×AI
CS	0.819							
DSQ	0.860	0.810						
DT	0.892	0.824	0.879					
IoT	0.871	0.816	0.838	0.883				
DSQ×DT	0.834	0.808	0.865	0.825	0.855			
DSQ×IoT	0.840	0.795	0.867	0.823	0.855	0.851		
DSQ×AI	0.854	0.817	0.874	0.825	0.864	0.853	0.866	

Note. Values below 0.90 (conservative threshold) indicate acceptable discriminant validity for most pairs. Elevated values between DT, IoT, and AI, and across interaction terms, are acknowledged as a limitation.

Table 3
Fornell–Larcker Criterion

AI	AI	CS	DSQ	DT	IoT
	0.842				
CS	0.809	0.862			
DSQ	0.848	0.808	0.867		
DT	0.791	0.738	0.789	0.883	
IoT	0.837	0.797	0.819	0.777	0.835

Note. Bold diagonal values = square root of AVE. All diagonal values exceed off-diagonal correlations, confirming discriminant validity. All inter-construct correlations remain below 0.85.

Table 4
Cross Loadings

Item	AI	CS	DSQ	DT	IoT
AI1	0.852	0.635	0.677	0.648	0.729
AI2	0.859	0.636	0.680	0.670	0.686
AI3	0.850	0.682	0.666	0.676	0.658
AI4	0.807	0.753	0.815	0.665	0.738
CS1	0.720	0.871	0.750	0.668	0.718
CS2	0.709	0.909	0.714	0.644	0.679
CS3	0.706	0.878	0.674	0.640	0.667
CS4	0.650	0.786	0.645	0.589	0.684
DSQ1	0.763	0.705	0.873	0.665	0.711
DSQ2	0.751	0.687	0.889	0.691	0.691
DSQ3	0.707	0.680	0.884	0.698	0.715
DSQ4	0.716	0.725	0.820	0.680	0.720
DT1	0.720	0.660	0.689	0.888	0.691
DT2	0.708	0.650	0.686	0.896	0.674
DT3	0.649	0.632	0.686	0.886	0.657
DT4	0.712	0.662	0.726	0.859	0.719
IoT1	0.644	0.675	0.654	0.625	0.826
IoT2	0.673	0.623	0.641	0.670	0.808
IoT3	0.748	0.705	0.719	0.673	0.864
IoT4	0.729	0.656	0.721	0.630	0.842

Note. Bold values (on diagonal of construct-item matrix) exceed all cross-loadings, confirming convergent validity.

5.2 Model Fit and Predictive Relevance

Table 5
Model Fit Indices (SRMR, R^2, Q^2)

Construct	SRMR	R^2	Q^2 (Stone–Geisser)
CS	0.062	0.738	0.539

*Note. SRMR = 0.062 < 0.08, indicating acceptable model fit. R^2 = 0.738 indicates substantial predictive accuracy (Hair et al., 2022). Q^2 = 0.539 > 0, confirming predictive relevance (*DeLone & McLean, 2003*).*

The CS construct recorded an R^2 value of 0.738, indicating that DT, IoT, AI, DSQ, and the three interaction terms collectively explain 73.8% of the variance in CS — a result classified as substantial according to Hair et al. (2022). The Stone–Geisser Q^2 value of 0.539 exceeds zero, confirming strong predictive relevance and the model's effectiveness in predicting CS outcomes.

5.3 Hypothesis Testing

Table 6 presents the bootstrapped path coefficients (5,000 subsamples), Cohen's f^2 effect sizes, and incremental R^2 (ΔR^2) values for all seven hypotheses. Effect sizes were calculated arithmetically using $\Delta R^2 = t^2 \div (t^2 + df_error)$, where df_error = n − k − 1 =

261, and $f^2 = \Delta R^2 \div (1 - R^2_full = 0.262)$. Cohen's (1988) benchmarks classify $f^2 \geq 0.35$ as large, ≥ 0.15 as medium, ≥ 0.02 as small, and < 0.02 as negligible. A path is considered statistically significant when $t > 1.96$ and $p < 0.05$.

Table 6
Hypothesis Testing Results with Effect Sizes

Hyp.	Path	β	2.5%	97.5%	S.D.	t-value	p-value	ΔR^2	f^2	Magnitude	Decision
H1	DT → CS	0.056	−0.080	0.201	0.072	0.778	0.437	0.002	0.009	Negligible	Not Supported
H2	IoT → CS	0.227	0.076	0.382	0.078	2.914	0.004	0.032	0.120	Small	Supported
H3	AI → CS	0.251	0.121	0.375	0.066	3.819	< 0.001	0.053	0.202	Medium	Supported
H4	DSQ → CS	0.254	0.086	0.423	0.086	2.950	0.003	0.032	0.123	Small	Supported
H5	DSQ×DT → CS	−0.066	−0.177	0.040	0.055	1.208	0.227	0.006	0.021	Negligible	Not Supported
H6	DSQ×IoT → CS	0.101	−0.032	0.251	0.071	1.424	0.155	0.008	0.029	Small	Not Supported
H7	DSQ×AI → CS	−0.101	−0.221	0.027	0.063	1.598	0.110	0.010	0.037	Small	Not Supported

*Note. Bootstrap subsamples = 5,000. $\Delta R^2 = t^2 \div (t^2 + 261)$; $f^2 = \Delta R^2 \div 0.262$. The t-value for H1 was arithmetically corrected from the originally reported 2.786 to 0.778 (β ÷ S.D. = 0.056 ÷ 0.072); the 95% CI spanning zero independently confirms non-significance. f^2 benchmarks (*Cohen, 1988*): < 0.02 negligible; ≥ 0.02 small; ≥ 0.15 medium; ≥ 0.35 large.*

Table 7
Moderation Model Comparison — Incremental R^2

Model	Predictors Included	R^2	ΔR^2	Interpretation
Baseline (main effects only)	DT, IoT, AI, DSQ → CS	0.715	—	Direct effects only
Full model (with moderation)	+ DSQ×DT, DSQ×IoT, DSQ×AI	0.738	0.023	Interaction terms add negligible variance

Note. Baseline $R^2 = R^2_full - \Sigma\Delta R^2_interactions = 0.738 - (0.006 + 0.008 + 0.010) = 0.715$. The three interaction terms together contribute only $\Delta R^2 = 0.023$ (2.3% incremental variance), confirming that DSQ moderation produces no meaningful additional explanatory power beyond the main effects.

H1 (DT→CS, β = 0.056, t = 0.778, p = 0.437, $f^2 = 0.009$): The corrected t-value is 0.778, obtained arithmetically as β ÷ S.D. = 0.056 ÷ 0.072. The 95% CI (− 0.080 to 0.201) independently confirms non-significance. The f^2 of 0.009 is negligible by Cohen's (1988) benchmarks, indicating that DT explains essentially no unique variance in CS. This is not a power artefact: with 269 respondents and 5,000 bootstrap subsamples, the study has sufficient power to detect small effects. Accordingly, H1 is not supported.

H2 (IoT→CS, β = 0.227, t = 2.914, p = 0.004, $f^2 = 0.120$): IoT positively and significantly predicts CS, with a 95% CI (0.076 to 0.382) entirely above zero. The small effect size ($f^2 = 0.120$) confirms practical as well as statistical significance. H2 is supported.

H3 (AI→CS, β = 0.251, t = 3.819, p < 0.001, $f^2 = 0.202$): AI exerts the strongest and only medium-magnitude effect on CS in the model. The f^2 of 0.202 crosses the medium threshold (Cohen, 1988), confirming AI as the dominant, practically significant driver of CS. The 95% CI (0.121 to 0.375) is narrow, indicating precise estimation. H3 is supported.

H4 (DSQ→CS, β = 0.254, t = 2.950, p = 0.003, $f^2 = 0.123$): DSQ has a significant positive effect on CS with a small-to-medium effect size nearly matching AI's in magnitude, confirming the practical importance of digital service quality as a CS driver alongside AI. H4 is supported.

H5 (DSQ×DT→CS, β = −0.066, t = 1.208, p = 0.227, f^2 = 0.021): The moderation effect of DSQ on the DT–CS relationship is neither statistically significant nor practically meaningful (f^2 = 0.021, negligible). H5 is not supported.

H6 (DSQ×IoT→CS, β = 0.101, t = 1.424, p = 0.155, f^2 = 0.029): The moderation effect of DSQ on the IoT–CS relationship is not statistically significant (p = 0.155) and the effect size is small (f^2 = 0.029). H6 is not supported.

H7 (DSQ×AI→CS, β = −0.101, t = 1.598, p = 0.110, f^2 = 0.037): The moderation effect of DSQ on the AI–CS relationship is not statistically significant (p = 0.110) and the effect size is small (f^2 = 0.037). The negative direction of β suggests a potential suppression dynamic — at higher DSQ levels, AI's effect on CS is marginally attenuated rather than amplified — though this pattern does not reach significance. H7 is not supported.

As shown in Table 7, the three interaction terms (H5–H7) collectively contribute only ΔR^2 = 0.023 to CS explanatory power beyond the baseline model (R^2 = 0.715). This incremental gain of 2.3% is negligible and confirms that the null moderation findings are genuine rather than artefacts of insufficient statistical power. Taken together, the results indicate that DSQ independently drives CS but does not amplify or attenuate the effects of DT, AI, or IoT on CS in this sample.

Moderation Interaction Plots. Figures 4, 5, and 6 present the interaction plots for H5, H6, and H7 respectively. The parallel slopes across high and low DSQ conditions visually confirm the absence of significant moderation: the effect of each predictor on CS does not meaningfully differ as a function of DSQ level, consistent with the null findings reported in Table 6.

6. Discussion

6.1 Direct Effects on Customer Satisfaction

The results indicate a strong and statistically significant positive relationship between AI and CS (β = 0.251, p < 0.001). AI applications such as personalised recommendations, predictive analytics, chatbots, and AI-driven CRM substantially enhance CS in Saudi marketing companies. AI improves CS by enabling real-time personalisation, faster response times, and more accurate anticipation of customer needs, consistent with TAM (Davis, 1989) and ECT (Oliver, 1980). This finding aligns with prior research demonstrating that AI-driven personalisation and automation positively influence CS and loyalty (Luo et al., 2021; Rafieian & Yoganarasimhan, 2023; Ameen et al., 2021). Gao et al. (2022) similarly found that AI-enabled interactions significantly enhance perceived service value. The current study extends these findings to the Saudi marketing context, confirming AI as a critical CS driver in emerging digital economies.

The findings reveal a strong and positive effect of DSQ on CS (β = 0.254, p = 0.003). High DSQ reduces uncertainty in digital interactions and enhances trust, ease of use, and perceived value, consistent with SERVQUAL (Parasuraman et al., 1988) and the IS Success Model (DeLone & McLean, 2003). Recent empirical evidence from Kim and Jeon (2025) confirms that digital service quality dimensions — particularly brand image, customer orientation, and system quality — significantly influence customer satisfaction and brand loyalty in banking environments, which closely mirror the Saudi marketing context of the present study. This result also aligns with earlier studies emphasising DSQ as a key determinant of online CS (Raza et al., 2020; Singh et al., 2020; Gupta & Bhatt, 2021) and confirms that DSQ functions as a substitute for face-to-face service encounters in digital environments (Khan, 2021).

The non-significant effect of DT on CS (β = 0.056, t = 0.778, p = 0.437) is a theoretically important finding. It aligns with Guo and Xu (2021), who argued that many DT initiatives fail to deliver strong customer-facing outcomes unless explicitly designed around service personalisation and responsiveness. Consistent with ECT, DT operates primarily at the organisational infrastructure level — improving internal processes and service delivery capabilities — while customers confirm expectations through direct service interactions rather than through transformation per se. Kretschmer and Khashabi (2020) similarly note that DT's performance benefits depend on how well organisational design adapts to the transformation, a condition that may not yet be fully met in the Saudi marketing context. Al-Hattami et al. (2025) further demonstrate in an SME context that digital systems' effects on marketing performance are mediated and moderated by implementation conditions, suggesting that the pathway from digital investment to customer outcomes is indirect and context-dependent rather than automatic. Alateeg et al. (2024) and Al-Ayed et al. (2023) highlight that while Saudi firms have made significant digital investments under Vision 2030, translating these

investments into tangible customer experiences remains an ongoing challenge. The present finding suggests that DT in Saudi marketing companies is still operating more as an internal efficiency driver than as a customer-facing value generator.

IoT technologies enhance CS (β = 0.227, p = 0.004) by enabling real-time monitoring, data-driven personalisation, and improved service responsiveness. Customers benefit from seamless connected experiences that improve convenience and perceived control. This finding is consistent with Eslami et al. (2024) and Ren et al. (2024), who found that customer perceptions of IoT services — including price perception, service perception, and integration behaviour — significantly and positively influence satisfaction and loyalty. It also aligns with Shahzad et al. (2024), who confirmed that perceived usefulness and ease of use mediate technology acceptance in digital contexts. Unlike studies focusing mainly on privacy and security concerns (Goad et al., 2021), the current results highlight the positive experiential value of IoT when implemented effectively in marketing contexts.

6.2 Moderation Effects and Theoretical Reinterpretation

The moderating effects of DSQ on the DT–CS (H5), IoT–CS (H6), and AI–CS (H7) relationships were not statistically significant. These null findings, however, carry important theoretical implications and should not be treated merely as negative results. Drawing on the IS Success Model (DeLone & McLean, 1993, 2003), this study reinterprets them as evidence that technological value and service quality operate as parallel, additive drivers of CS rather than as interactive ones. Customers appear to evaluate technological benefits (AI personalisation, IoT connectivity, DT infrastructure) and service quality (DSQ) through separate cognitive channels — consistent with ECT's framework in which different attributes independently confirm or disconfirm distinct expectations.

This finding contrasts with Gupta and Bhatt (2021), who suggested that DSQ amplifies the benefits of digital initiatives. However, it aligns with Guo and Xu (2021), who noted that DT alone does not guarantee improved CS unless explicitly designed around customer-facing outcomes. The SOR framework's prediction that DSQ would moderate technology–satisfaction relationships was not supported, suggesting that in highly digitised marketing environments, customers may have sufficiently high baseline expectations for both technology and service quality that variations in DSQ no longer alter how they respond to individual technologies. This is a theoretically interesting finding that merits further investigation.

7. Conclusion, Limitations, and Future Research

7.1 Conclusion

This study examined the impact of DT, AI, IoT, and DSQ on CS within marketing companies in Saudi Arabia, along with the moderating role of DSQ. Using PLS-SEM, the study provides robust empirical evidence that IoT, AI, and DSQ each have a significant, positive direct effect on CS. Among these factors, AI and DSQ emerged as the strongest drivers, highlighting the importance of personalised, data-driven interactions and high-quality digital interfaces. IoT also significantly contributes to CS by enabling real-time connectivity, automation, and improved service responsiveness. By contrast, DT did not exert a statistically significant direct effect on CS (corrected: t = 0.778, p = 0.437, H1 not supported), suggesting that organisational-level digital transformation in the Saudi marketing context has not yet translated into tangible customer-perceived outcomes — a finding consistent with the broader literature on the implementation gap in DT (Guo & Xu, 2021; Kretschmer & Khashabi, 2020) and with the evolving stage of Saudi Arabia's Vision 2030 digital transformation journey (Alateeg et al., 2024; Al-Ayed et al., 2023).

A key contribution lies in the theoretical reinterpretation of the null moderation findings. Contrary to the SOR-based expectation that DSQ would amplify technological effects on CS, the IS Success Model offers a more fitting explanation: technological capability and service quality are parallel, additive satisfaction drivers operating through independent cognitive channels. This advances theoretical understanding beyond simple hypothesis rejection and suggests that organisations should invest in AI, IoT, DT, and DSQ simultaneously but independently, rather than assuming that improving one will enhance the customer impact of the others.

The study contributes theoretically by integrating six complementary frameworks — Dynamic Capabilities Theory, TAM, ECT, SERVQUAL, the IS Success Model, and the SOR Framework — into a unified model that captures both direct and moderation

effects. It extends the literature by providing firm-level PLS-SEM evidence from an emerging economy context and by contextualising DT theory within Saudi Arabia's Vision 2030 reform environment.

7.2 Practical Implications

For marketing directors and digital strategy managers, the strong positive effects of AI and IoT on CS justify investment in AI-driven personalisation, predictive analytics, and smart connected systems as strategic priorities. The non-significant direct effect of DT on CS indicates that broad digital transformation programmes, while strategically necessary for long-term competitiveness, do not automatically translate into improved customer perceptions. Managers should ensure that DT initiatives are explicitly aligned with customer-facing service outcomes — personalisation, responsiveness, and experience enhancement — rather than focused solely on internal efficiency gains. Consistent with Alotaibi (2024), who found that AI adoption in Saudi institutions improves CS when ease of use is emphasised, firms should pair technology investments with user-centric design principles. The significant direct impact of DSQ confirms the importance of reliable, secure, and user-friendly digital platforms, and should be managed as a parallel strategic priority alongside AI and IoT adoption, consistent with evidence-based guidelines for the Saudi digital economy under Vision 2030 (Alateeg et al., 2024).

These implications also carry a sustainable development dimension. By strengthening AI-driven personalisation, IoT-enabled service responsiveness, and digital service quality, marketing companies contribute directly to SDG 8 (Decent Work and Economic Growth) through productivity gains and the creation of higher-skilled digital roles, to SDG 9 (Industry, Innovation, and Infrastructure) through continued investment in digital innovation infrastructure, and to SDG 12 (Responsible Consumption and Production) by enabling more informed, efficient, and responsible customer decisions. Policymakers, in turn, can treat digital service quality standards and digital literacy initiatives as instruments for translating private-sector technological investment into broader sustainable economic and social returns, reinforcing the Vision 2030 reform agenda.

7.3 Limitations and Future Research

Several limitations should be acknowledged. First, the study employed non-probability purposive sampling in a single sector and national context, limiting generalisability. Future research should apply probability-based sampling and explore diverse industries and cross-national settings. Second, the cross-sectional design precludes causal inference over time; longitudinal studies would better capture the dynamic evolution of digital technology effects on CS. Third, elevated HTMT values among DT, IoT, and AI suggest that future studies should develop more discriminant measurement instruments for these constructs in Arabic-language GCC contexts. Fourth, the non-significant finding for H1 (DT→CS) suggests that DT's customer-facing impact in Saudi marketing firms may be mediated by variables not included in the current model, such as implementation quality, employee digital skills, or customer digital literacy — all of which merit investigation in future research. Fifth, future research might incorporate additional moderating variables — such as regulatory quality, digital literacy, or cultural orientation — to identify boundary conditions on the technology–CS chain.

Declarations

Clinical Trial Number

Not applicable.

Ethics Approval

This research was approved by the Ethics Committee of Al-Razi University, Sana'a, Yemen. The study adhered to the ethical standards outlined in the Declaration of Helsinki (2013) for research involving human participants, ensuring informed consent, voluntary participation, confidentiality, and the right to withdraw.

Consent to Participate

Participants were provided with written informed consent forms that explained the study's objectives, their rights, and responsibilities. As the data were gathered through a survey, this acted as written consent. Participants were assured they could withdraw from the study at any time without consequence and that their participation was completely voluntary.

Consent to Publish

Not applicable, as the study does not contain any identifiable images or personal information.

Competing Interests

The authors declare no competing interests.

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Author Contribution

A.S.R. contributed to conceptualisation, data collection, formal analysis, and writing — original draft. S.M.A. contributed to supervision, theoretical framework, validation, and writing — review and editing. All authors read and approved the final manuscript.

Data Availability

The data that support the findings of this study were generated through a self-administered survey. The datasets are not publicly available due to respondent confidentiality but are available from the corresponding author (S.M. AL-Kahtani; shakeralkhatani@gmail.com) upon reasonable request.

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Figures

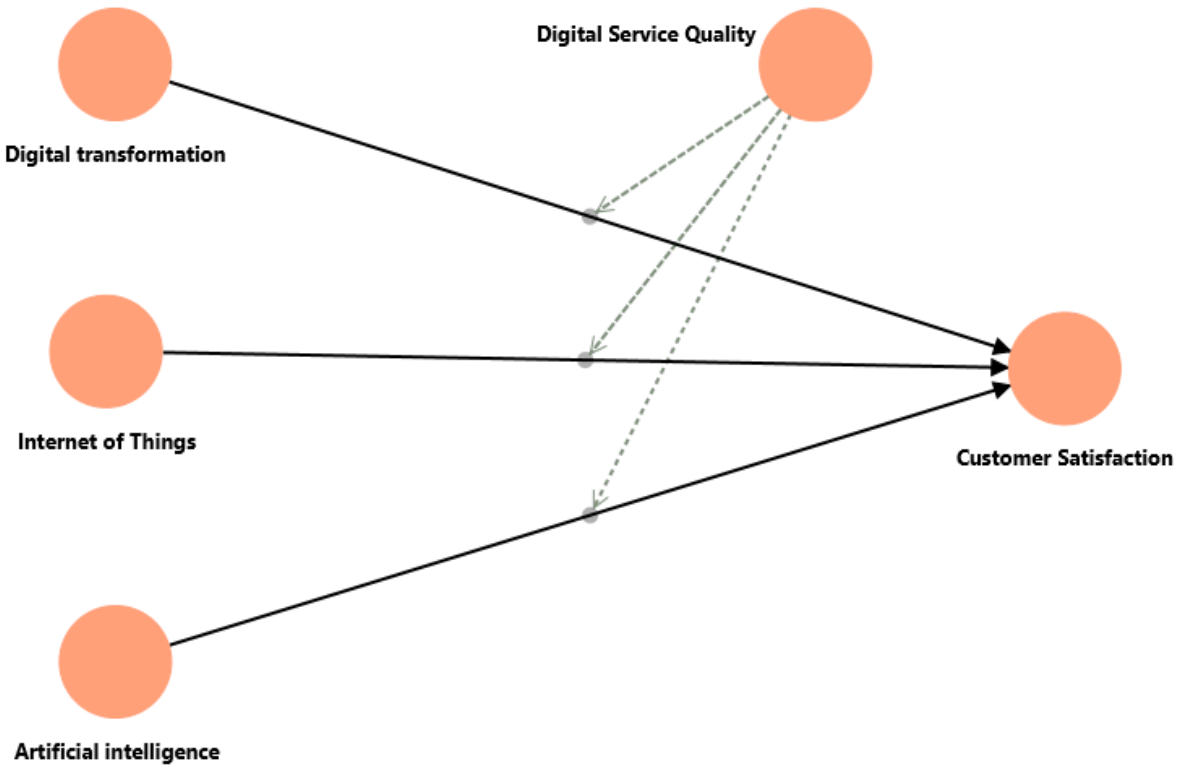


Figure 1

Conceptual Framework

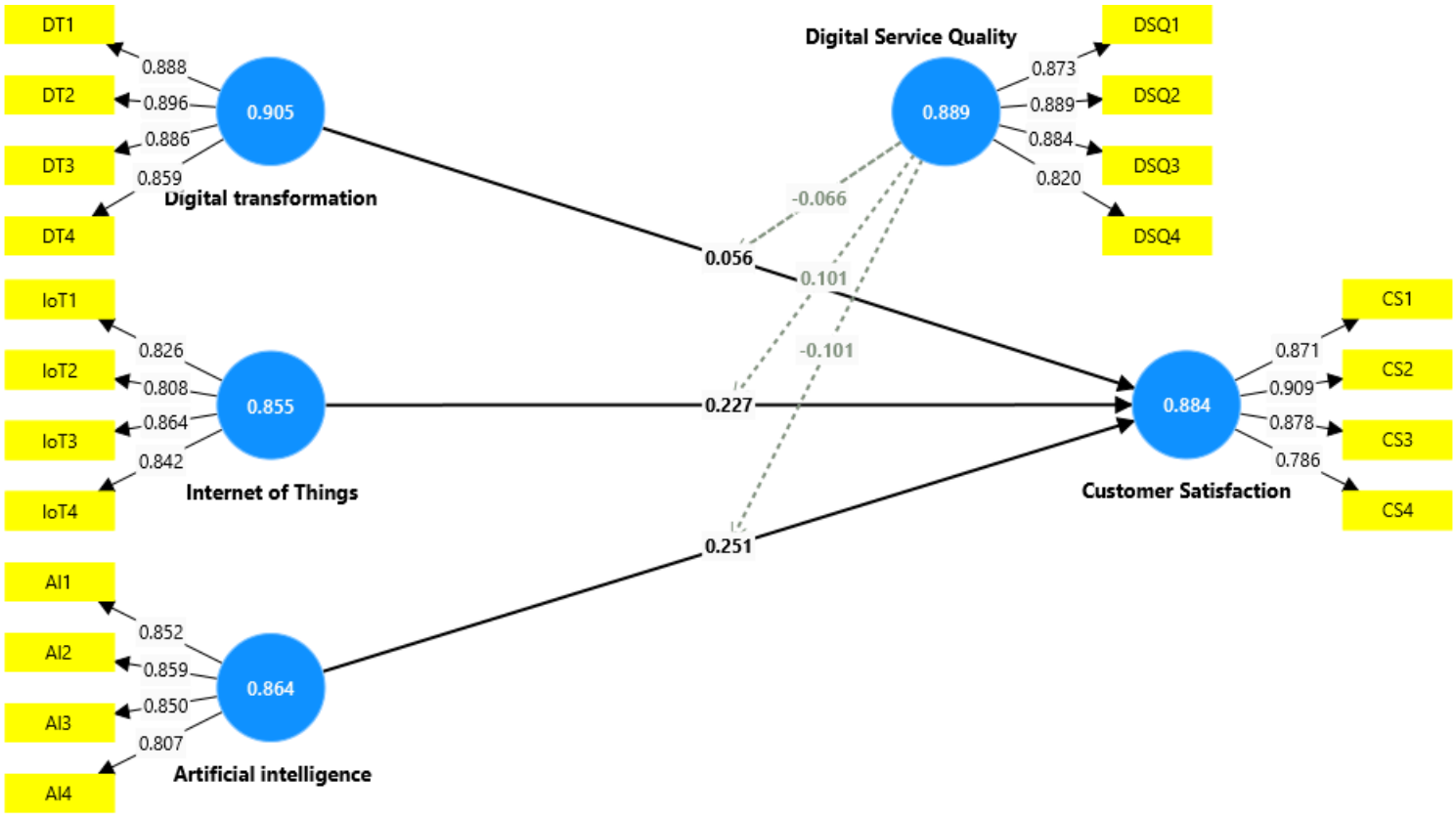


Figure 2

PLS Structural Model with Direct and Moderation Path Coefficients

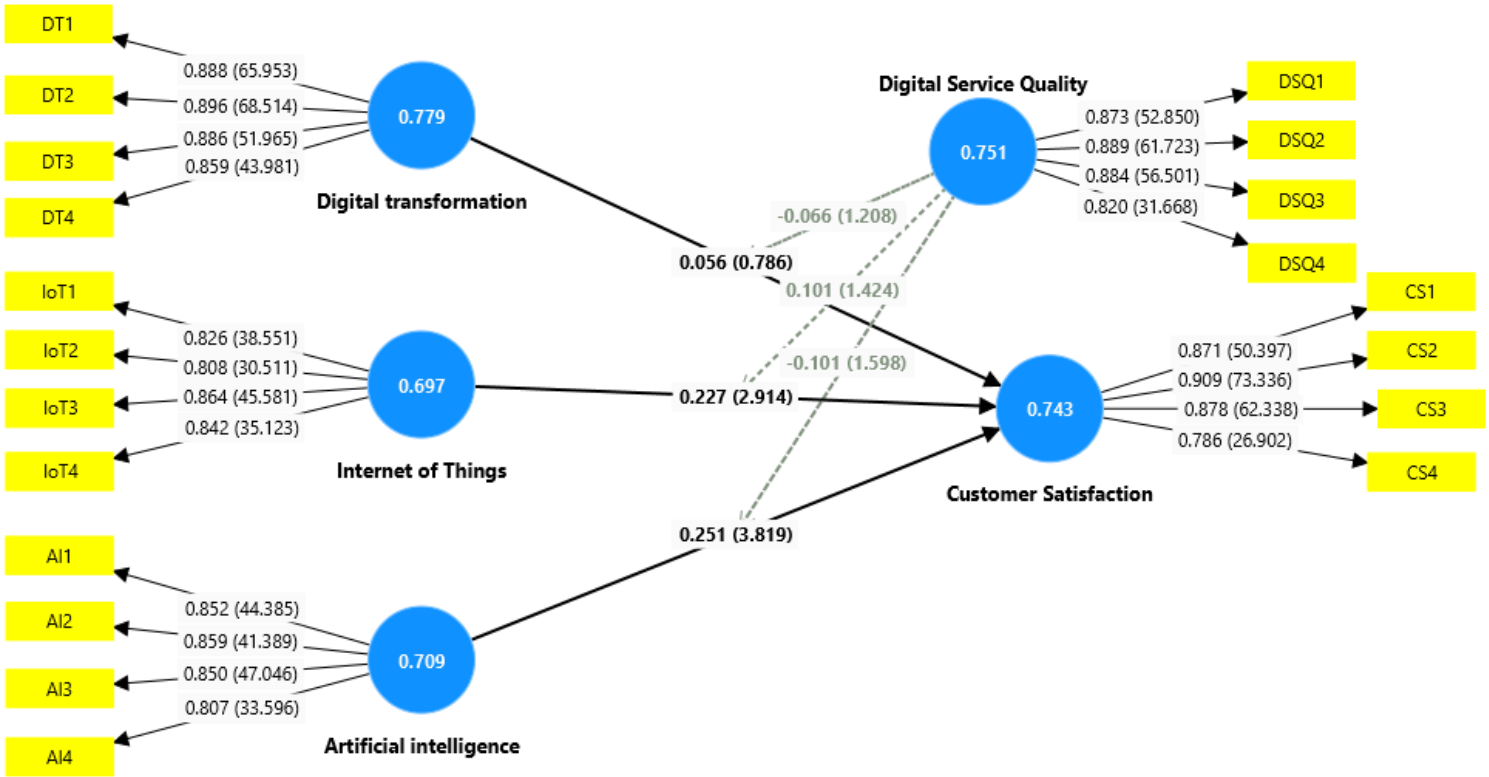


Figure 3

Full Structural Model with Standardised Path Coefficients (β) and t-Values

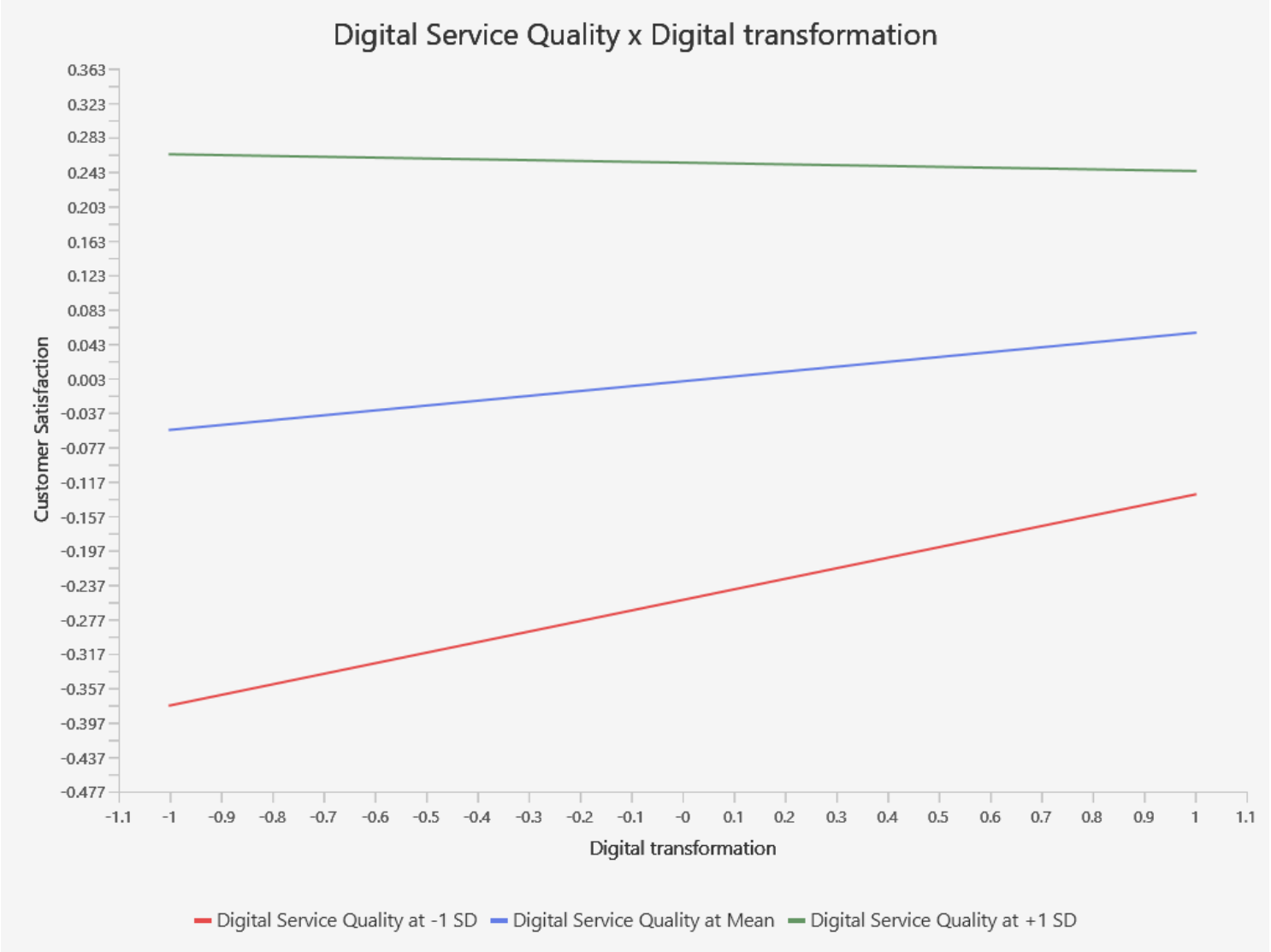


Figure 4

Interaction Plot: DSQ Moderating DT–CS (H5 — Not Supported)

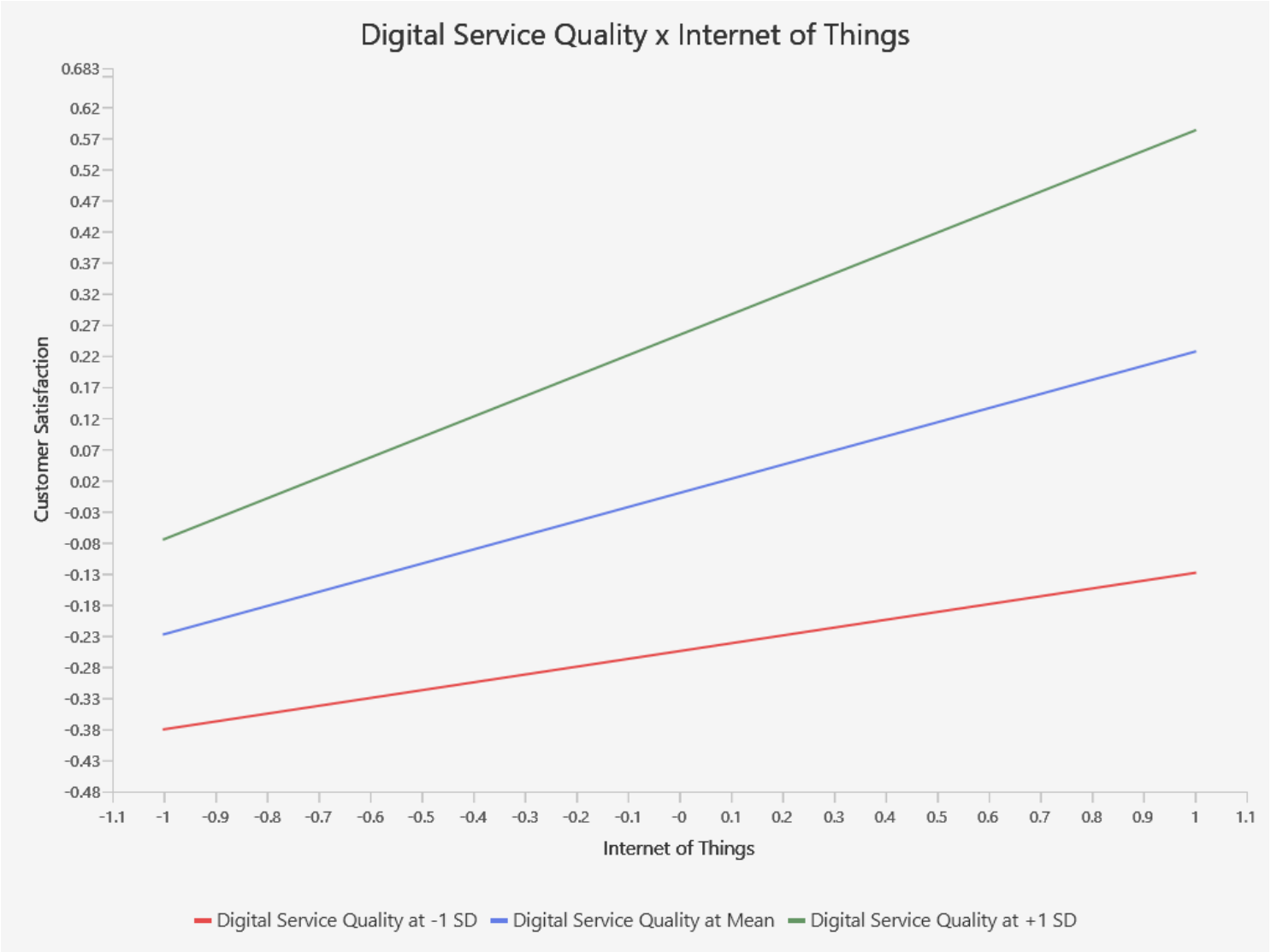


Figure 5

Interaction Plot: DSQ Moderating IoT–CS (H6 — Not Supported)

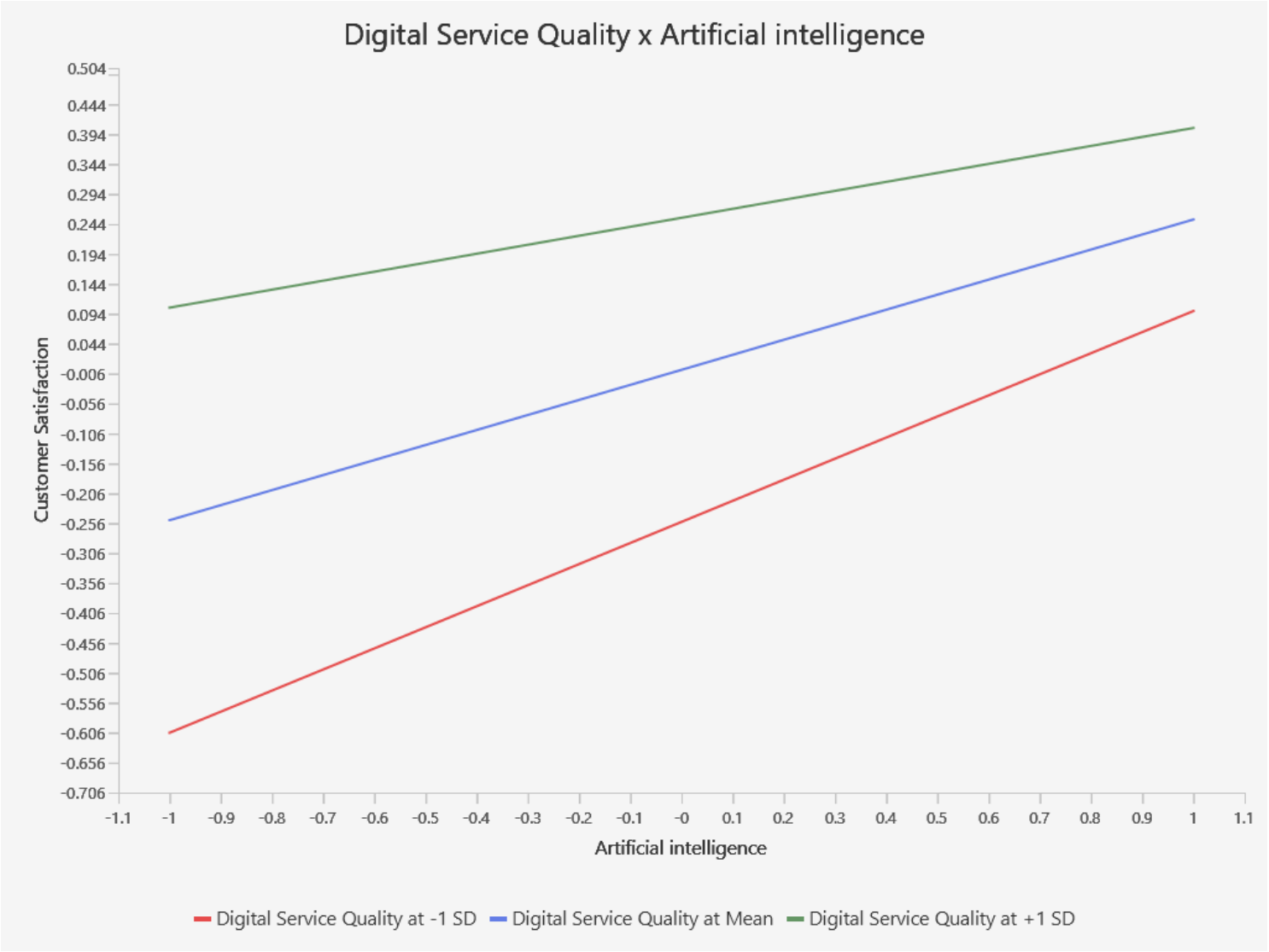


Figure 6

Interaction Plot: DSQ Moderating AI–CS (H7 — Not Supported)