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Impact of Technology Transfer on the Quality of Care in Moroccan Healthcare Institutions

BENNANI Fatima Zahra[1], DAKKAK Badr[2]

[1] Laboratory for Mathematics and Computer Science, Management and Finance, Electrical Engineering and Physical Sciences, EMSI-Marrakech, Morocco

[2] Cadi Ayyad University, National School of Applied Sciences of Marrakech, Engineering Systems and Applications Laboratory, Morocco

Abstract: This article examines the influence of technology transfer on healthcare quality in Moroccan healthcare institutions, jointly testing the mediating role of digital health innovation and the moderating role of organizational absorptive capacity. Data were collected through a structured questionnaire administered to 200 healthcare professionals (hospital directors, physicians, nursing managers, quality officers, and information-system managers) across university hospitals, public hospitals, private clinics, and health centres in Morocco, and analysed using a variance-based structural modelling approach (composite scores, standardized regression, and bootstrapping) consistent with PLS-SEM logic [1]. The measurement model shows satisfactory reliability and convergent validity (Cronbach's alpha ranging from 0.887 to 0.928; AVE ranging from 0.689 to 0.776), although discriminant validity among the antecedent constructs remains limited, warranting cautious interpretation of construct-specific effects. The structural model explains a substantial share of variance in technology transfer ($R^2 = 0.852$), digital health innovation ($R^2 = 0.807$), and healthcare quality ($R^2 = 0.876$). Training, leadership, digital infrastructure, and university-hospital partnerships each positively and significantly predict technology transfer, which in turn positively affects digital health innovation; digital innovation positively affects healthcare quality and partially mediates the technology transfer-quality relationship. However, the hypothesized moderating effect of absorptive capacity on the technology transfer-innovation link is not statistically supported. The study offers one of the few joint empirical tests of the TOE framework, the Resource-Based View, and absorptive capacity theory in the Moroccan hospital sector, and transparently discusses discriminant-validity limitations often left unaddressed in comparable studies.

Keywords: Technology transfer; digital health innovation; healthcare quality; absorptive capacity; PLS-SEM; healthcare institutions

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1. Introduction

For the past two decades, healthcare system performance has been a central concern of public policy in emerging countries [2]. In Morocco, healthcare system reform has accelerated since 2020 around three structuring initiatives that define the institutional framework within which this research is situated: the generalization of health coverage (AMO Tadamon, more than 11 million additional beneficiaries), the digitalization of hospital services, driven notably by the shared electronic medical record and the national interoperability platform GISRE, and the development of telemedicine, whose regulatory framework was established by Decree No. 2-22-754 of 2023. The budget allocated to the health sector was, moreover, raised to approximately 30.9 billion dirhams in 2024, a 55% increase relative to 2021, reflecting an unprecedented financial effort toward modernizing the care system.

This technological investment effort does not, however, translate mechanically into a uniform improvement in the quality of care. Consistent with broader observations on the digital transformation of health systems in low- and middle-income countries [3], [4], several recent studies on the digital transition of the Moroccan health system point to fragmented implementation, persistent gaps between institutions, and recurring obstacles related to governance, interoperability, staff digital literacy, and funding sustainability [5]. This apparent paradox (rising technological investment for uneven quality gains) constitutes the starting point of this research, which seeks to shed light on the underlying organizational mechanisms rather than merely noting a correlation between budgetary effort and quality outcomes.

2. Problem Statement, Research Questions, and Objectives

The literature on technology adoption in healthcare has long focused on the technical determinants of technology transfer (equipment availability, funding, infrastructure), paying more limited attention to the organizational mechanisms through which this transfer does, or does not, translate into an effective improvement in quality of care [6]. Yet a now well-established theoretical stream in information systems and innovation management, grounded notably in absorptive capacity theory [7] and the Technology-Organization-Environment framework [8], shows that the value of a technology lies not in its acquisition but in the organization's capacity to recognize, assimilate, and exploit it. Applied to the hospital sector, this observation suggests that digital health innovation (telemedicine, medical artificial intelligence, electronic medical records, mobile applications) constitutes the intermediate mechanism through which technology transfer converts into quality gains, and that this conversion itself depends on institutions' organizational absorptive capacity.

Three shortcomings can be identified in the existing literature, which jointly motivate the design of this study. Empirical studies simultaneously testing a mediating effect “through digital innovation” and a moderating effect “trough absorptive capacity” in the relationship between technology transfer and quality of care remain rare, with most research testing these two mechanisms separately rather than within an integrated model. Furthermore, research jointly mobilizing the TOE, RBV, and absorptive capacity frameworks in the hospital sector of emerging countries, particularly in the Maghreb, remains scarce, with most available studies focusing on the Gulf countries, South Asia, or sub-Saharan Africa. Finally, a significant portion of studies on absorptive capacity in digital health treat it alternately as a direct antecedent, a mediator, or a moderator, without empirical consensus emerging on its precise role in the causal chain [9] ; a question this study addresses directly by explicitly testing its moderating role rather than presupposing it.

This threefold observation leads to the following central research question: to what extent do the organizational determinants of technology transfer influence the quality of care in Moroccan healthcare institutions, and through what mechanisms (mediating, via digital innovation, and moderating, via absorptive capacity) does this relationship operate? Answering this question is of twofold interest.

Theoretically, it allows an empirical test, in a still under-documented context, of the articulation between these three conceptual frameworks. Managerially and in terms of public policy, it provides Moroccan hospital decision-makers with benchmarks for prioritizing their technological and organizational investments, in line with the Health 2025-2030 strategy.

This central question breaks down into four complementary research questions, concerning respectively the organizational determinants of technology transfer in Moroccan healthcare institutions, this transfer's capacity to foster digital health innovation, this innovation's ability to improve quality of care and mediate the relationship between technology transfer and quality of care, and finally the possible reinforcement, through absorptive capacity, of the effect of technology transfer on digital innovation. The main research objective, which follows directly, is to analyse the influence of technology transfer on quality of care in Moroccan healthcare institutions; it breaks down into five specific objectives, namely identifying the organizational factors that foster technology transfer, assessing the effect of this transfer on digital health innovation, measuring the impact of digital innovation on quality of care, testing the latter's mediating role, and testing the moderating role of absorptive capacity.

3. Literature Review and Theoretical Framework

3.1. The Technology-Organization-Environment (TOE) Framework

Developed by Tornatzky and Fleischer [8], the Technology-Organization-Environment (TOE) framework explains an organization's adoption of a technological innovation through three interacting contexts: the technological context, which covers available internal technologies and externally accessible technologies on the market; the organizational context, which refers to the size, resources, structure, leadership quality, and culture of the organization; and the environmental context, which includes competitive pressure, regulation, and external partnerships. This framework has been widely used in studies on hospital digital transformation [6], with several studies showing that the technological maturity of healthcare institutions jointly depends on the availability of digital infrastructure and organizational factors such as staff training and managerial support. In the model tested here, digital infrastructure corresponds to the technological context, training and leadership to the organizational context, and university-hospital-enterprise partnerships to the environmental context, offering a relatively complete operationalization of the three dimensions of the TOE framework as applied to the Moroccan hospital setting.

3.2. The Resource-Based View and the Knowledge-Based View

Resource-Based View (RBV) theory, formalized by Barney [10], posits that an organization's competitive advantage rests on resources exhibiting four attributes: value, rarity, inimitability, and non-substitutability. Applied to the hospital context, this perspective invites us to view technology transfer not as a mere acquisition of equipment "easily imitated by competing institutions" but as a process of building distinctive organizational capabilities, such as staff digital competencies, innovation governance, or strategic partnerships. The Knowledge-Based View, an extension of the RBV proposed by Grant [11], extends this approach by positioning knowledge as the most decisive strategic resource for organizational performance. It justifies, in the model tested, the importance given to continuous training and knowledge sharing as antecedents of technology transfer, as well as to the "assimilation" dimension of absorptive capacity, which constitutes precisely the junction point between the Knowledge-Based View and absorptive capacity theory discussed below.

3.3. Absorptive Capacity Theory

Introduced by Cohen and Levinthal [7], absorptive capacity (ACAP) refers to an organization's ability to recognize the value of new external knowledge, assimilate it, and exploit it for operational purposes. Zahra and George [12] later distinguished a potential absorptive capacity, encompassing acquisition and assimilation, from a realized absorptive capacity, encompassing transformation and exploitation a distinction reflected in the measurement instrument used here, which covers all four dimensions of the construct. This theory has been widely applied in research on digital health (eHealth) technology adoption: some studies show that organizational absorptive capacity, combined with information-system governance, conditions the effective exploitation of digital innovations by healthcare institutions, while more recent work links absorptive capacity to the resilience and safety of digitized care pathways, introducing the notion of patient-knowledge-specific absorptive capacity [9]. In the broader field of international technology transfer, a recent study shows that firms' absorptive capacity and collaborative practices mediate rather than moderate; the relationship between technology transfer and innovation performance, a finding that will directly inform, in Section 7, the discussion of the absence of moderation observed in the present sample.

3.4. Diffusion of Innovations and Digital Health Innovation

Rogers's [13] diffusion of innovations theory explains how an innovation spreads within a social system as a function of its perceived relative advantage, compatibility with existing practices, complexity, trialability, and observability. This reading is echoed, at the individual level, by technology acceptance models such as the Technology Acceptance Model [14] and its extension, the Unified Theory of Acceptance and Use of Technology [15], which emphasize perceived usefulness and perceived ease of use as proximal determinants of individual adoption two dimensions consistent with the complexity and relative advantage attributes retained by Rogers [13] at the organizational level. Applied to digital health, this dual reading clarifies why some innovations, such as teleconsultation, diffuse more rapidly than others, such as medical artificial intelligence, whose perceived complexity and clinical liability concerns slow adoption. In the model tested, digital health innovation is operationalized through five dimensions: telemedicine, medical artificial intelligence, clinical big data, the electronic medical record, and mobile patient-monitoring applications. Recent literature on the digital transformation of health systems shows that these innovations contribute to improved clinical outcomes and patient experience when accompanied by adequate organizational adaptation [16].

3.5. Quality of Care: Conceptual Framework

Donabedian's [17], [18] structure-process-outcome model remains the dominant reference for conceptualizing quality of care: structure refers to institutions' resources and organization, which digital infrastructure and staff competencies directly fall under; processes refer to the care activities themselves, which digital innovation transforms, for example through clinical decision support; and outcomes refer to effects on patient health and satisfaction. This framework is echoed in DeLone and McLean's [19] information systems success model, which links system and information quality to net benefits for the organization and end user a causal chain structurally close to the one tested here between technology transfer, digital innovation, and quality of care. In this study, quality of care is measured through five dimensions consistent with Donabedian's framework: care safety, speed of care, patient satisfaction, continuity of care, and clinical effectiveness; the latter dimension referring directly to outcomes in Donabedian's sense, while safety and continuity relate more to processes.

3.6. Technology Transfer in Healthcare in Emerging Countries

Several recent empirical studies conducted in developing-country contexts comparable to Morocco confirm the importance of organizational factors in the success of technology transfer in healthcare. A study conducted in the Bangladeshi healthcare sector, using an ISM-DEMATEL approach, identifies management support, political support, funding, and the availability of technological infrastructure as critical success factors for technology transfer. Another study, focusing on health information infrastructures in developing countries, distinguishes mere technology transfer from technological learning, emphasizing that the successful scaling of telemedicine services depends more on local organizational dynamics than on the technical transfer itself. Research conducted in the Saudi hospital sector shows that knowledge-transfer mechanisms mediate the relationship between leadership and the digital performance of healthcare institutions a finding conceptually close to the mediating role attributed here to digital innovation. More broadly, in low- and middle-income countries, Alami et al. [4] emphasize that the introduction of artificial intelligence technologies in healthcare can only produce sustainable and equitable benefits if accompanied by a parallel strengthening of local organizational capabilities, an argument that directly structures the articulation between technology transfer and absorptive capacity retained in this article's conceptual model.

3.7. The Moroccan Context of Hospital Digitalization

In Morocco, the available literature documents significant but uneven progress in hospital digitalization: the progressive generalization of the shared electronic medical record, the deployment of the national interoperability platform GISRE, the teleconsultation regulatory framework introduced in 2023 [20], and persistent territorial disparities in access to specialized care, with nearly 270 rural municipalities remaining more than an hour from a hospital institution. Chafiq et al. [21], drawing on the case of the cardiology department of the Ibn Sina University Hospital in Rabat, concretely illustrate how the introduction of digital technologies transforms clinical practices while running up against local organizational constraints corroborating, at the scale of a hospital department, the broader observations made by Jallal et al. [5] on the digital transition of the Moroccan health system: fragmented implementation, governance coordination difficulties, uneven digital literacy among health professionals, and long-term funding challenges. These findings reinforce the relevance of the model tested here, which articulates precisely the organizational factors (training, leadership, partnerships) likely to explain this heterogeneity, while situating the present study directly within the continuity of this empirical work centred on the Moroccan context.

3.8. Common Method Bias in Studies of This Type

Studies based on self-administered questionnaires, which measure predictor and outcome variables simultaneously from the same respondent, are exposed to a risk of common method bias, which can artificially inflate correlations between constructs [22]. This risk, real in most published studies of this type in the health sector, is explicitly tested in the Results section of this article by means of Harman’s single-factor test, in line with standard methodological recommendations.

3.9. Literature Review Synthesis and Study Positioning

Table 1 summarizes the main findings of the literature review, the limitations identified, and the way in which the present study seeks to address them, before the conceptual model and the resulting hypotheses are presented in detail in the next section.

Table 1: Synthesis of the literature review and positioning of the study.

Theoretical axis	Main finding from the literature	Limitation identified / study positioning
TOE framework	Technology adoption conditioned by the technological, organizational, and environmental contexts	Complete operationalization of the three dimensions in the Moroccan hospital context, still under-documented
RBV / Knowledge-Based View	Organizational advantage based on rare and inimitable resources and knowledge	Application to healthcare technology transfer as a capability-building process, not a mere equipment acquisition
Absorptive capacity	Role treated as direct, mediating, or moderating depending on the study; little consensus	Explicit test of the moderating role (rather than presupposed) on the technology transfer-innovation relationship

Diffusion of innovation / digital innovation	Diffusion conditioned by perceived relative advantage, compatibility, and complexity of the innovation	Five-dimension operationalization (telemedicine, AI, big data, EMR, mobile applications) rarely combined in a single instrument
Quality of care (Donabedian [17], [18])	Quality structured into structure, process, outcomes	Instrument covering all three components (safety, continuity = process; clinical effectiveness = outcome; satisfaction = perceived outcome)
Moroccan context / emerging countries	Real but heterogeneous digital progress; governance and digital literacy still developing	First joint empirical test of TOE-RBV-ACAP in the Moroccan hospital sector, with transparency regarding discriminant-validity limitations

4. Conceptual Model and Research Hypotheses

The conceptual model mobilized articulates four organizational determinants of technology transfer (training, leadership, digital infrastructure, and university-hospital partnerships), a mediating variable (digital health innovation), a dependent variable (quality of care), and a moderating variable (absorptive capacity), whose effect is postulated on the relationship between technology transfer and digital innovation. This model was calibrated to the structure of the available data; it does not retain innovation culture as a separate antecedent, as this dimension was not the subject of a separate measure in the instrument used to collect the data analysed.

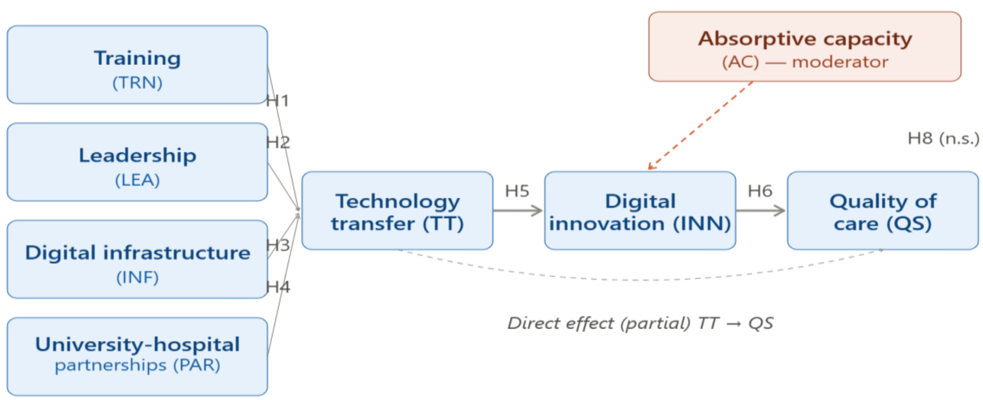

Figure 1. Conceptual research model: antecedents of technology transfer, mediation by digital innovation, and moderation by absorptive capacity.

4.1. Hypothesis Development

This conceptual model translates into eight research hypotheses, organized into three blocks that reproduce the sequential logic of the model: antecedents of technology transfer, cascading effects up to quality of care, and then mediation and moderation mechanisms. Regarding the antecedents, health-personnel training continuous training, digital skills, equipment training is expected to have a positive effect on technology transfer (H1), as is leadership, understood as strategic vision, managerial support, and resource allocation (H2), digital infrastructure, comprising the electronic medical record, the IT network, and interoperability (H3), and university-hospital-enterprise partnerships (H4).

Regarding the cascading effects toward quality of care, technology transfer is expected to have a positive effect on digital health innovation (H5), which is in turn expected to have a positive effect on quality of care (H6). Finally, regarding the mediation and moderation mechanisms, digital health innovation is expected to mediate the relationship between technology transfer and quality of care (H7), while absorptive capacity is expected to positively moderate the relationship between technology transfer and digital innovation, such that the higher an institution's absorptive capacity, the stronger the effect of technology transfer on digital innovation would be (H8).

5. Research Methodology and Data Collection

5.1. Epistemological Positioning and Research Design

This research is grounded in a positivist paradigm and adopts a quantitative, hypothetico-deductive approach: a conceptual model is built from the literature and then subjected to an empirical test aimed at statistically confirming or disconfirming each of the hypotheses formulated. The research design is cross-sectional, as the data were collected at a single point in time rather than longitudinally, a limitation discussed in Section 7.

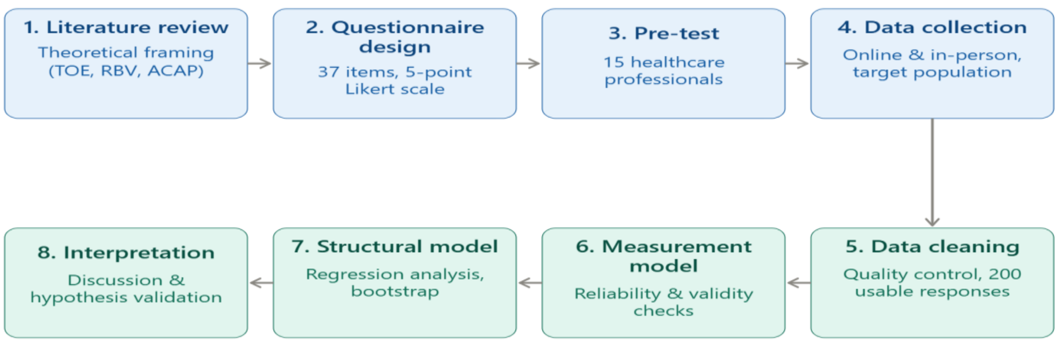

Figure 2. Methodological approach and data-collection steps.

5.2. Population, Sampling, and Unit of Analysis

The target population consists of healthcare professionals working in university hospitals, public hospitals, private clinics, and health centres in Morocco, occupying institutional management, medical or nursing supervision, quality management, or information-systems management functions; that is, the actors directly involved in decisions and practices relating to technology transfer and digital innovation. The unit of analysis is therefore the individual respondent, whose responses are assumed to reflect the situation of their institution.

Sampling was carried out using a non-probabilistic convenience method, complemented by a diversification approach that intentionally sought respondents from different institution categories (university hospitals, public hospitals, private clinics, health centres) in order to limit, as far as possible, excessive sample homogeneity. The final analysed sample comprises 200 usable respondents. This size is deemed sufficient in light of the usual sizing rules for variance-based structural equation modelling: it is well above the minimum required by the "10 cases per indicator" rule applied to the most complex construct in the model, which comprises five indicators, and, for a medium effect size ($f^2 \approx 0.15$) and a 5% significance threshold, allows a statistical power greater than 0.95 to be reached for the highest number of predictors in the model, namely the four antecedents of technology transfer [1].

5.3. Measurement Instrument and Operationalization of Constructs

Data were collected using a structured questionnaire comprising 37 items across eight constructs, measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The scales were adapted from the literature mobilized in Section 3; the TOE framework for the organizational antecedents, Zahra and George [12] for the four dimensions of absorptive capacity, Rogers [13] for the dimensions of digital innovation, and Donabedian [18] for the dimensions of quality of care ; hen reworded and contextualized for the Moroccan hospital sector. Table 2 presents the operationalization adopted for each of the eight constructs.

Table 2: Operationalization of the model's constructs.

Construct	Role in the model	No. of items	Dimensions / example indicators
Training (TRA)	Antecedent (independent)	4	Continuous training; digital skills; equipment training
Leadership (LEA)	Antecedent (independent)	4	Strategic vision; management support; resource allocation
Digital infrastructure (INF)	Antecedent (independent)	5	Electronic medical record; IT network; interoperability
Partnerships (PAR)	Antecedent (independent)	4	Universities; medical enterprises; research centres
Technology transfer (TT)	Central variable	5	Acquisition and deployment of medical and digital technologies
Absorptive capacity (AC)	Moderator	5	Acquisition; assimilation; transformation; exploitation
Digital health innovation (INN)	Mediator	5	Telemedicine; medical AI; big data; EMR; mobile applications
Quality of care (QoC)	Dependent	5	Safety; speed; satisfaction; continuity; clinical effectiveness

5.4. Data Collection Procedure

The questionnaire was pre-tested with a small group of healthcare professionals to verify the clarity of the wording, completion time, and contextual relevance of the items; the minor adjustments identified at this stage were incorporated into the final version of the instrument. Data collection was then administered directly to respondents, in accordance with the principles of informed consent, response anonymity, and confidentiality of the data collected, consistent with the requirements of Moroccan Law No. 09-08 on the protection of personal data. No nominative or directly identifying information was collected; only aggregated data, not traceable to a specific individual or institution, were retained for analysis.

5.5. Data Analysis Method

The analysis follows the methodological logic of variance-based structural equation modelling (PLS-SEM; [23], [1]), in two stages: assessment of the measurement model (reliability, convergent and discriminant validity), followed by assessment of the structural model (path coefficients, R^2, mediation and moderation testing). For methodological transparency, it should be noted that the indicators were computed from composite scores that is, the mean of the items per construct and standardized linear regressions, complemented by a bootstrap resampling procedure with 5,000 replications for testing the indirect effect, following the now-standard logic of bootstrapped confidence-interval mediation testing methods [24]. This approach reproduces the estimation logic of PLS-SEM (indicator weighting, standardized path coefficients, bootstrapping) without, however, substituting for estimation by a full iterative PLS algorithm, for example under SmartPLS [25] or ADANCO, which future research may use to confirm and refine the results obtained here.

5.6. Common Method Bias Control Procedures

In line with the recommendations of Podsakoff et al. [22], several procedural precautions were taken prior to data collection, such as guaranteeing anonymity to reduce social desirability, physically separating the questionnaire blocks relating to the predictor variables and the dependent variable, and rewording certain items to limit anchoring effects. An ex post statistical test, Harman's single-factor test, was also performed and is reported in Section 6.3, in the interest of transparency regarding the limitations it reveals.

6. Results

6.1. Measurement Model Assessment

Table 3 presents the internal consistency and convergent validity indicators for the model's eight constructs. All constructs meet the usual thresholds retained in the methodological literature; Cronbach's alpha and composite reliability (CR) above 0.70 [26], and average variance extracted (AVE) above 0.50 [1] indicating satisfactory reliability and convergent validity for the measurement model as a whole.

Table 3: Reliability and convergent validity of the measurement model. Note. Usual thresholds: Cronbach's alpha ≥ 0.70; CR ≥ 0.70; AVE ≥ 0.50 [1], [26].

Construct	No. of items	Cronbach's alpha	Composite reliability (CR)	AVE
Training (TRA)	4	0.895	0.927	0.762
Leadership (LEA)	4	0.887	0.922	0.748
Digital infrastructure (INF)	5	0.887	0.917	0.689
Partnerships (PAR)	4	0.887	0.922	0.747
Technology transfer (TT)	5	0.917	0.938	0.751
Absorptive capacity (AC)	5	0.913	0.935	0.742
Digital innovation (INN)	5	0.916	0.937	0.750
Quality of care (QoC)	5	0.928	0.945	0.776

6.2. Discriminant Validity

Discriminant validity was assessed using the Fornell and Larcker [27] criterion and the HTMT (Heterotrait-Monotrait) ratio [28]. Table 4 presents the inter-construct correlations (off-diagonal) and the square root of the AVE (diagonal, in bold).

Table 4: Inter-construct correlations (off-diagonal) and square root of the AVE (diagonal).

	TRA	LEA	INF	PAR	TT	AC	INN	QoC
TRA	0.873							
LEA	0.874	0.865						
INF	0.882	0.894	0.830					
PAR	0.863	0.881	0.895	0.864				
TT	0.864	0.878	0.894	0.885	0.867			
AC	0.833	0.854	0.881	0.883	0.906	0.861		
INN	0.839	0.862	0.881	0.887	0.898	0.894	0.866	
QoC	0.837	0.843	0.879	0.856	0.905	0.891	0.918	0.881

The Fornell-Larcker criterion requires that the square root of each construct's AVE exceed its correlations with other constructs. This criterion is only partially satisfied here: for several construct pairs, notably TT-QoC, INN-QoC, and TT-AC, the inter-construct correlation exceeds the square root of the AVE. The HTMT ratio confirms this finding, with computed values ranging from 0.918 to 1.008, well above the conservative 0.85 threshold recommended by Henseler et al. [28]. This twofold result indicates that discriminant validity among the model's antecedent constructs is not fully established in this sample, a limitation that is revisited and discussed in depth in the overall assessment proposed in Section 7.5.

6.3. Common Method Bias Test

A Harman single-factor test was performed on all 37 items. The first factor extracted accounts for 66.6% of total variance, above the conventional 50% threshold below which common method bias is generally considered non-problematic. This result, combined with the discriminant-validity difficulties noted above, constitutes an important limitation of the study, discussed in Section 7 and revisited in Section 8.3; it invites interpretation of the model's structural coefficients as trend indications rather than as estimates of fully independent net effects, as several antecedent constructs are strongly correlated with one another a point confirmed by the multicollinearity analysis presented below.

6.4. Structural Model and Hypothesis Testing

The structural model was estimated in three stages: the regression of technology transfer on its four antecedents; the regression of digital innovation on technology transfer and its interaction with absorptive capacity; and the regression of quality of care on digital innovation, controlling for technology transfer to test mediation. The variance inflation factors (VIF) of the four antecedents of technology transfer are high, ranging from 5.67 to 7.46, confirming strong collinearity among training, leadership, digital infrastructure, and partnerships, consistent with the limited discriminant validity established above. Table 5 presents the results of the hypothesis tests relating to the structural model.

The model explains a substantial share of the variance in the endogenous variables: $R^2 = 0.852$ (adjusted $R^2 = 0.849$) for technology transfer, $R^2 = 0.807$ for digital innovation, and $R^2 = 0.876$ for quality of care in the model integrating both technology transfer and digital innovation. These values reflect a high explanatory power of the conceptual model tested, which should nonetheless be interpreted in light of the methodological reservations raised above regarding discriminant validity and common method bias.

Table 5: Structural model results and hypothesis testing. R^2: Technology transfer = 0.852 (adjusted R^2 = 0.849); Digital innovation = 0.807; Quality of care (TT + INN model) = 0.876.

Hyp.	Relationship	Standardized β	t	p	Decision
H1	Training → Technology transfer	0.166	2.53	0.012	Supported
H2	Leadership → Technology transfer	0.210	2.96	0.003	Supported
H3	Digital infrastructure → Technology transfer	0.311	4.13	< 0.001	Supported
H4	Partnerships → Technology transfer	0.278	4.01	< 0.001	Supported
H5	Technology transfer → Digital innovation	0.898	28.74	< 0.001	Supported
H6	Digital innovation → Quality of care (controlling for TT)	0.540	9.47	< 0.001	Supported
H8	Technology transfer × Absorptive capacity → Digital innovation	0.009	0.30	0.767	Not supported

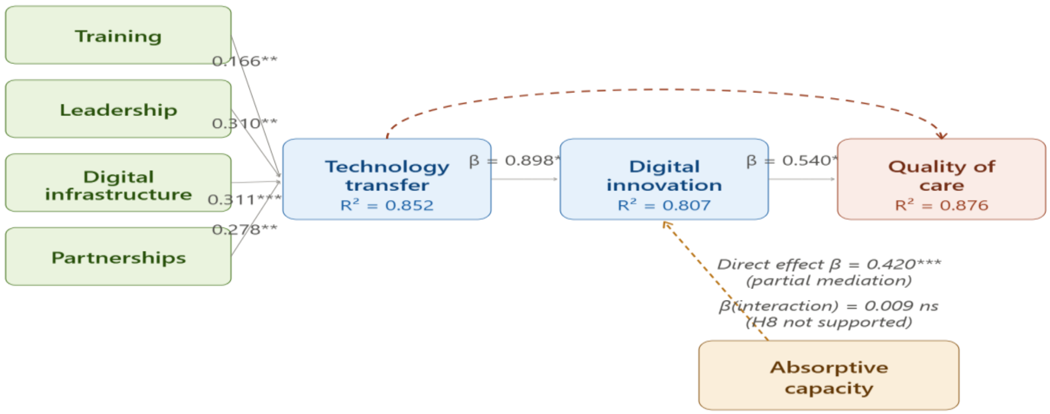

Figure 3. Estimated structural model, standardized path coefficients, and significance.

6.5. Mediation Test (H7)

The indirect effect of technology transfer on quality of care, via digital innovation, was estimated by bootstrapping with 5,000 replications, using sampling with replacement. The standardized indirect effect is 0.485, with a 95% confidence interval of [0.370; 0.604], which excludes zero: the mediation effect is therefore statistically significant. The direct effect of technology transfer on quality of care, controlling for digital innovation, also remains significant ($\beta = 0.420$, $p < 0.001$). Digital innovation therefore exerts a partial “not total” mediation of the relationship between technology transfer and quality of care, consistent with the total-effect decomposition logic proposed by Preacher and Hayes [24]: hypothesis H7 is thus supported.

6.6. Moderation Test (H8)

Contrary to expectations, the interaction term between technology transfer and absorptive capacity on digital innovation is not statistically significant ($\beta = 0.009$, $t = 0.30$, $p = 0.767$). Absorptive capacity does, however, exert a significant positive direct effect on digital innovation ($\beta = 0.448$, $p < 0.001$), but does not moderate, in this sample, the strength of the relationship between technology transfer and digital innovation. Hypothesis H8 is therefore not supported; the theoretical implications of this counter-intuitive finding are developed in detail in Section 7.4.

6.7. Summary of Results

Seven of the eight hypotheses formulated are statistically supported, as summarized in Table 6 below; only the absorptive-capacity moderation hypothesis (H8) is rejected, a result whose theoretical significance is discussed as a whole in Section 7.

Table 6: Summary of hypothesis testing.

Hypothesis	Statement (summary)	Decision
H1	Training → Technology transfer (+)	Accepted
H2	Leadership → Technology transfer (+)	Accepted
H3	Digital infrastructure → Technology transfer (+)	Accepted
H4	Partnerships → Technology transfer (+)	Accepted
H5	Technology transfer → Digital innovation (+)	Accepted
H6	Digital innovation → Quality of care (+)	Accepted
H7	Mediation by digital innovation (TT → INN → QoC)	Accepted (partial mediation)

H8	Moderation by absorptive capacity (TT × AC → INN)	Rejected

Beyond the simple acceptance-or-rejection reading, an overall examination of Table 6 reveals a coherent results architecture, structured into three blocks whose relative intensity deserves emphasis before the in-depth discussion in Section 7. The first block, relating to the four organizational antecedents of technology transfer (H1-H4), brings together effects that are all positive and significant, but moderate and hierarchically ordered in magnitude, with digital infrastructure ($\beta = 0.311$) and university-hospital-enterprise partnerships ($\beta = 0.278$) clearly ahead of leadership ($\beta = 0.210$) and training ($\beta = 0.166$). This hierarchy, which might seem merely descriptive, in fact indicates that technology transfer in the Moroccan institutions studied rests more on external, infrastructural resources than on internal managerial dynamics; a nuance that structures the entire discussion of determinants in Section 7.1.

The second block, relating to the core of the model (H5 and H6), yields a markedly different picture: the effects here are not only significant but substantially larger in magnitude than those of the first block, particularly for the relationship between technology transfer and digital innovation ($\beta = 0.898$), which constitutes the highest coefficient in the entire structural model. This difference in intensity between the two blocks is not theoretically trivial: it suggests that, once the organizational conditions for transfer are in place, the conversion of that transfer into digital innovation and then into quality gains follows an almost mechanical logic, whereas the initial establishment of these organizational conditions remains more uncertain and more dependent on each institution's specific configuration. The mediation test (H7) complements this second block by clarifying the nature of the mechanism linking technology transfer and quality of care: the significant indirect effect (0.485; 95% CI [0.370; 0.604]), combined with the persistence of a significant direct effect ($\beta = 0.420$), establishes that this is a partial "not total" mediation, a finding that qualifies any reading that would make digital innovation the sole channel of transformation for quality of care.

The third block, the moderation test (H8), introduces a break from the overall coherence described above: while the first seven hypotheses confirm a causal chain broadly consistent with theoretical expectations, the absence of an interaction effect between technology transfer and absorptive capacity ($\beta = 0.009$, $p = 0.767$) contradicts the hypothesis well-grounded in the literature mobilized in Section 3.3, that absorptive capacity would amplify the conversion of technology transfer into digital innovation. This result should not, however, be read in isolation: it must be considered alongside the significant direct effect of absorptive capacity on digital innovation ($\beta = 0.448$, $p < 0.001$), which suggests that this variable acts, in this sample, as a parallel antecedent rather than as an amplifier a distinction whose full theoretical implications are developed in Section 7.4.

Taken together, these three blocks depict a model in which quality of care ultimately appears as the outcome of a technologically and organizationally intensive chain (training, leadership, infrastructure, and partnerships producing technology transfer), which in turn produces, with particularly strong intensity, digital innovation "itself a driver of quality gains" while the role of absorptive capacity, far from playing the expected amplifying role, is limited to that of a direct and autonomous determinant of digital innovation. It is this overall architecture, coherent in its central causal component yet surprising in its moderating component, that the next section discusses in light of the literature mobilized in Sections 2 and 3.

7. Discussion of Results

This section discusses each of the results obtained in light of the literature mobilized in Sections 2 and 3, highlighting convergences, nuances, and divergences with prior work, before proposing, in Section 7.5, an overall reading of the tested model that articulates the structural results with the methodological reservations noted in Section 6.

7.1. The Determinants of Technology Transfer (H1 to H4)

The four antecedents tested each exert a positive and statistically significant effect on technology transfer, with a relative-importance ranking of digital infrastructure ($\beta = 0.311$) above partnerships ($\beta = 0.278$), themselves above leadership ($\beta = 0.210$), itself above training ($\beta = 0.166$). This ranking is broadly consistent with the postulates of the TOE framework [8], which assigns a central role to the technological and environmental dimensions in highly regulated and institutionalized sectors such as healthcare. The pre-eminence of digital infrastructure aligns with findings in the literature on Moroccan hospital digitalization, which identifies the deployment of the national interoperability platform GISRE and the shared electronic medical record as essential technical prerequisites for any technology-transfer strategy [5]. The relative importance of university-hospital-enterprise partnerships, greater than that of leadership and training in this sample, also echoes work highlighting the role of institutional collaborations foundations, universities, technology companies in accessing resources and competencies unavailable internally, a mechanism that absorptive capacity theory precisely describes as the acquisition of external knowledge [12]. This finding nonetheless qualifies certain studies that place managerial leadership at the forefront of the determinants of technology adoption in healthcare [15]: in the Moroccan context studied here, it is technological resources and external alliances that appear to drive technology transfer to a greater extent, which may reflect a context in which infrastructure constraints remain the primary limiting factor, even ahead of internal steering capabilities.

7.2. The Effect of Technology Transfer on Digital Innovation (H5)

The very strongly positive effect of technology transfer on digital innovation ($\beta = 0.898$, $R^2 = 0.807$) unambiguously confirms hypothesis H5 and aligns with Rogers's [13] diffusion of innovations theory, according to which the acquisition of a technology constitutes the first-order condition for the emergence of new usage practices a reading also compatible with the TAM's [14] emphasis on perceived usefulness as a precondition for the effective appropriation of a digital tool. This result is also consistent with work showing that the integration of medical technologies, such as the electronic medical record or interoperability platforms, fosters the emergence of new clinical and organizational processes such as telemedicine or clinical decision support [21]. The magnitude of this coefficient, the highest in the entire structural model, suggests that, in the context studied, digital innovation remains largely dependent on initial technology transfer rather than on an autonomous internal innovation process consistent with a health system in a phase of technological catch-up rather than mature diffusion.

7.3. The Effect of Digital Innovation on Quality of Care and Its Mediation (H6, H7)

Digital innovation exerts a positive and significant effect on quality of care, whether in the direct model ($\beta = 0.918$) or in the model controlling for technology transfer ($\beta = 0.540$). This result confirms H6 and aligns with the "process-outcome" component of Donabedian's model [17], [18]: telemedicine, medical artificial intelligence, and the electronic medical record improve coordination among professionals, reduce the risk of error, and speed up care, three mechanisms directly associated with the safety, speed, and continuity-of-care dimensions measured in this study, and which align with the net-benefits logic described by DeLone and McLean [19] in the broader field of information systems. The mediation test further confirms that digital innovation partially "not totally" mediates the relationship between technology transfer and quality of care (indirect effect = 0.485, 95% CI [0.370; 0.604]; residual direct effect = 0.420, $p < 0.001$): H7 is therefore supported, but in a nuanced form. This partial-mediation result diverges from conceptual models including the one initially sketched for this work that sometimes present digital innovation as the exclusive vector of transformation for quality of care; it suggests instead that technology transfer also improves quality of care through channels not captured by digital innovation as measured here, for example the simple modernization of equipment and clinical protocols, independently of their properly innovative dimension.

7.4. The Absence of a Moderating Effect of Absorptive Capacity (H8)

The most notable, and most counter-intuitive, result in light of the literature mobilized concerns the failure to confirm the moderating effect of absorptive capacity on the relationship between technology transfer and digital innovation (interaction $\beta = 0.009$, $p = 0.767$). This result contrasts with work that, building on Zahra and George [12], links absorptive capacity to better exploitation of digital innovations in healthcare, as well as with studies linking absorptive capacity to the resilience of digital health systems [9]. Three explanations, not mutually exclusive, can be put forward, and deserve to be considered together rather than in isolation.

First, absorptive capacity exerts a strong direct effect on digital innovation in this sample ($\beta = 0.448$, $p < 0.001$), which may statistically reduce the residual variance available for an interaction effect: absorptive capacity would here act more as a parallel antecedent than as an amplifier of the technology transfer-innovation relationship a distinction already raised in theoretical debates on the additive versus multiplicative nature of ACAP effects, and one that interaction-term modelling, standard since Aiken and West [29], is precisely designed to resolve empirically. Second, the strong collinearity observed among the antecedent constructs (high variance inflation factors, limited discriminant validity, potential common method bias according to the Harman test) may statistically mask a genuine moderating effect by diluting its specific share of variance among strongly correlated main effects; this result should therefore be interpreted with caution and deserves to be retested on a sample with more discriminant psychometric properties. Third, the statistical power available to detect an interaction effect, generally lower than that required for main effects at an equal sample size, may have been insufficient in this sample of 200 respondents to detect a small-magnitude moderation effect, if one genuinely exists in the population studied. Taken together, these three explanations suggest that the rejection of H8 should not be interpreted as a general refutation of absorptive capacity theory, but rather as an invitation to further specify its boundary conditions in the Moroccan hospital context.

7.5. An Overall Reading: Global Coherence and Discriminant-Validity Limitations

Taken as a whole, the structural results confirm the coherence of the proposed theoretical architecture: the TOE framework for the antecedents, diffusion of innovation theory for the core of the model, and Donabedian's model for the dependent variable, while bringing an important nuance to absorptive capacity theory in its moderating role. This reading should nonetheless be tempered by the methodological reservations identified in Section 6: the limited discriminant validity among the antecedent constructs, with an HTMT close to or above 1, and the high level of variance explained by a single factor (66.6%), suggest that respondents may have perceived the constructs as partially redundant; a common limitation of studies based on multi-item scales administered to the same respondent at a single point in time [22]. This limitation does not invalidate the overall significance of the structural model, but calls for reading the relative coefficients among antecedents (H1 to H4) as trend indications rather than as estimates of strictly independent effects; a methodological reservation revisited in more operational terms in the limitations and future research avenues set out in Section 8.

8. Contributions of the Study

8.1. Theoretical Contributions

Theoretically, this research makes four main contributions, which respond to one another rather than simply adding up. It first offers an empirical test of a model jointly integrating technology transfer, digital health innovation, and quality of care in the Moroccan hospital context, still under-documented by the existing literature. It further jointly mobilizes the TOE, RBV, and Knowledge-Based View frameworks, diffusion of innovation theory, Donabedian's model, and absorptive capacity theory, rarely tested together in emerging countries, which highlights points of convergence and tension among these frameworks rather than mobilizing them in isolation. It also empirically highlights a partial mediation effect of digital innovation and an unconfirmed moderation effect of absorptive capacity, which qualifies part of the existing literature and opens research avenues on the boundary conditions of absorptive capacity theory in digital health. Finally, it offers a transparent demonstration, still rare in this type of study, of discriminant-validity limitations and the risk of common method bias, which contributes to the broader methodological debate on the robustness of PLS-SEM models in emerging-research contexts.

8.2. Managerial Contributions and Public Policy Implications

Managerially and in terms of public policy, these results invite Moroccan hospital decision-makers to prioritize investment in digital infrastructure and in university-hospital-enterprise partnerships, which appear as the levers most strongly associated with technology transfer in this sample, while accompanying these investments with continuous-training programmes and assertive managerial leadership, two determinants that are significant but of more modest magnitude. They also suggest not treating absorptive capacity as a mere automatic amplifier of the effects of technology transfer, but rather developing it as an autonomous lever, notably through training programmes specifically addressing the acquisition, assimilation, transformation, and exploitation of external technological knowledge. Finally, they argue for integrating digital-maturity and organizational-capacity indicators into the evaluation and accreditation frameworks for Moroccan healthcare institutions, in line with the orientations of the Health 2025-2030 strategy.

9. Conclusion

This study empirically tested, among 200 Moroccan healthcare professionals, a model linking the organizational determinants of technology transfer to quality of care, via the mediating role of digital health innovation and the postulated moderating role of absorptive capacity. Seven of the eight hypotheses formulated are statistically supported: training, leadership, digital infrastructure, and university-hospital partnerships positively influence technology transfer, which fosters digital innovation, which in turn improves quality of care, partially mediating the relationship between technology transfer and quality of care. The absorptive-capacity moderation hypothesis is, however, not confirmed in this sample, a result that qualifies part of the eHealth literature and opens research avenues on the conditions under which absorptive capacity acts as a direct antecedent rather than as an amplifier. These results, obtained with full methodological transparency regarding the discriminant-validity limitations of the measurement model, provide useful benchmarks for Moroccan hospital decision-makers, while opening research avenues to refine understanding of the mechanisms through which organizational absorptive capacity does, or does not, influence the valorization of technological investments in healthcare.

outline several avenues for future research that directly extend the contributions and methodological reservations set out above. A first avenue would consist of replicating the model on a larger sample stratified by institution type, incorporating sociodemographic control variables that would allow a multigroup analysis between public hospitals and private clinics. A second avenue would consist of retesting the moderating effect of absorptive capacity using measurement scales with stronger discriminant validity, for example by reducing the number of items shared across constructs or by using higher-order constructs. A third avenue would consist of using an Importance-Performance Map Analysis to identify priority levers for action for hospital managers, complementing the structural coefficients reported here. A fourth avenue would consist of studying a second, serial mediation mechanism (for example technology transfer, digital innovation, organizational learning, then quality of care) to refine understanding of the intermediate mechanisms. A final, qualitative avenue would consist of exploring, through interviews with institutional leadership, the reasons why absorptive capacity does not statistically moderate the tested relationship, in order to better understand its actual role in the Moroccan hospital context.

References

[1] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3rd ed. Thousand Oaks, CA, USA: Sage, 2022.

[2] A. I. Stoumpos, F. Kitsios, and M. A. Talias, “Digital transformation in healthcare: Technology acceptance and its applications,” Int. J. Environ. Res. Public Health, vol. 20, no. 4, p. 3407, 2023.

[3] H. Alami, M.-P. Gagnon, and J.-P. Fortin, “Digital health and the challenge of health systems transformation,” mHealth, vol. 3, p. 31, 2017.

[4] H. Alami, P. Lehoux, Y. Auclair, M. de Guise, M.-P. Gagnon, J. Shaw, et al., and R. Fleet, “Artificial intelligence in health care: Laying the foundation for responsible, sustainable, and inclusive innovation in low- and middle-income countries,” Global. Health, vol. 16, p. 52, 2020.

[5] M. Jallal, Z. Serhier, Z. Boubekri, H. Berrami, and M. Bennani Othmani, “Digital transition in healthcare in Morocco: Current progress and challenges to overcome,” in Proc. 9th Int. Congr. Inf. Commun. Technol. (ICICT), Lecture Notes in Networks and Systems, vol. 1055, Cham, Switzerland: Springer, 2024.

[6] R. Agarwal, G. Gao, C. DesRoches, and A. K. Jha, “Research commentary—The digital transformation of healthcare: Current status and the road ahead,” Inf. Syst. Res., vol. 21, no. 4, pp. 796–809, 2010.

[7] W. M. Cohen and D. A. Levinthal, “Absorptive capacity: A new perspective on learning and innovation,” Adm. Sci. Q., vol. 35, no. 1, pp. 128–152, 1990.

[8] L. G. Tornatzky and M. Fleischer, The Processes of Technological Innovation. Lexington, MA, USA: Lexington Books, 1990.

[9] I. Rubbio and M. Bruccoleri, “Unfolding the relationship between digital health and patient safety: The roles of absorptive capacity and healthcare resilience,” Technol. Forecast. Soc. Change, vol. 208, p. 123718, 2024.

[10] J. Barney, “Firm resources and sustained competitive advantage,” J. Manage., vol. 17, no. 1, pp. 99–120, 1991.

[11] R. M. Grant, “Toward a knowledge-based theory of the firm,” Strateg. Manage. J., vol. 17, no. S2, pp. 109–122, 1996.

[12] S. A. Zahra and G. George, “Absorptive capacity: A review, reconceptualization, and extension,” Acad. Manage. Rev., vol. 27, no. 2, pp. 185–203, 2002.

[13] E. M. Rogers, Diffusion of Innovations, 5th ed. New York, NY, USA: Free Press, 2003.

[14] F. D. Davis, “Perceived usefulness, perceived ease of use, and user acceptance of information technology,” MIS Q., vol. 13, no. 3, pp. 319–340, 1989.

[15] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of information technology: Toward a unified view,” MIS Q., vol. 27, no. 3, pp. 425–478, 2003.

[16] A. Ouajid, “Revolutionizing telemedicine: The impact of AI and AR in Moroccan healthcare,” J. Innov. Digit. Health, vol. 1, pp. 59–64, 2024.

[17] A. Donabedian, “Evaluating the quality of medical care,” Milbank Mem. Fund Q., vol. 44, no. 3, pp. 166–206, 1966.

[18] A. Donabedian, “The quality of care: How can it be assessed?,” JAMA, vol. 260, no. 12, pp. 1743–1748, 1988.

[19] W. H. DeLone and E. R. McLean, “The DeLone and McLean model of information systems success: A ten-year update,” J. Manage. Inf. Syst., vol. 19, no. 4, pp. 9–30, 2003.

[20] M. Jallal, Z. Serhier, H. Berrami, and M. Bennani Othmani, “Telemedicine: The situation in Morocco,” Stud. Health Technol. Inform., vol. 309, pp. 93–94, 2023.

[21] K. Chafiq, K. Dib, A. Zahidi, M. Cherti, A. Doukkali, and K. El Menzhi, "Les enjeux des nouvelles technologies numériques sur le système de santé marocain: Cas du service de cardiologie B du CHU Ibn Sina de Rabat," Ann. Cardiol. Angeiol., vol. 74, p. 101858, 2025.

[22] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: A critical review of the literature and recommended remedies," J. Appl. Psychol., vol. 88, no. 5, pp. 879–903, 2003.

[23] W. W. Chin, "The partial least squares approach for structural equation modeling," in Modern Methods for Business Research, G. A. Marcoulides, Ed. Mahwah, NJ, USA: Lawrence Erlbaum Associates, 1998, pp. 295–336.

[24] K. J. Preacher and A. F. Hayes, "Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models," Behav. Res. Methods, vol. 40, no. 3, pp. 879–891, 2008.

[25] C. M. Ringle, S. Wende, and J.-M. Becker, SmartPLS 3. Bönningstedt, Germany: SmartPLS GmbH, 2015.

[26] J. C. Nunnally and I. H. Bernstein, Psychometric Theory, 3rd ed. New York, NY, USA: McGraw-Hill, 1994.

[27] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," J. Mark. Res., vol. 18, no. 1, pp. 39–50, 1981.

[28] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," J. Acad. Mark. Sci., vol. 43, no. 1, pp. 115–135, 2015.

[29] L. S. Aiken and S. G. West, Multiple Regression: Testing and Interpreting Interactions. Newbury Park, CA, USA: Sage, 1991.