



Intelligent Enablers and Knowledge Application in Jordan's Smart Tourism Sector: The Mediating Role of Knowledge Sharing

Amer Alqudah

Isra University, Amman, Jordan

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ABSTRACT

Smart tourism organisations have significantly boosted investments in smart technologies, yet there is limited empirical evidence that illustrates how the different ones of these technologies have become (or not) a part of the knowledge application process, particularly in developing economies.. Drawing on the Knowledge-Based View (KBV) and Dynamic Capabilities Theory, this study examines the influence of three intelligent enablers—intelligent trust, intelligent infrastructure and intelligent capability—on knowledge application, and the mediating role of knowledge sharing in this relationship within Jordan's smart tourism sector. A cross sectional quantitative design was used. A total of 285 staff members from various luxury hotels, travel agencies, online tourism platforms and tourism technology providers in Jordan were surveyed. The models were tested by partial Least Squares Structural Equation Modelling (PLS-SEM); bootstrapping (5,000 resamples) was used for mediation analysis. The three intelligent enablers all have significant positive impacts on knowledge sharing, with intelligent capability ($\beta = 0.405$) having the biggest impact, followed by intelligent infrastructure ($\beta = 0.306$) and intelligent trust ($\beta = 0.300$). As a mediating variable, knowledge sharing has strong positive influence with knowledge application ($\beta = 0.568$) and partially mediates between every intelligent enabler with knowledge application. The model explained 64.2% of variance in knowledge sharing, and 73.9% of variance in knowledge application. For tourism organisations looking to translate investments in intelligent technology into tangible knowledge outcomes, they should focus on developing employees' intelligent capabilities via specific digital training and enhance and reinforce the intelligent infrastructure and create a 'psychological safety' by making the data-governance process transparent. This study is one of the first to combine three different types of intelligent enablers in one single model within the context of mediation and knowledge-based approach, and to prove it in the context of smart tourism in a developing economy. It shows that intelligent resources have only a limited impact on knowledge application by mechanisms of knowledge-sharing rather than directly through the use of technology.

1. INTRODUCTION

The tourism industry is undergoing one of the most far-reaching digital transformations of any service sector, as artificial intelligence (AI), big-data

analytics, cloud computing and the Internet of Things (IoT) become embedded in the core of how destinations and firms create value (Gretzel et al., 2015; Buhalis & Sinarta, 2019). These technologies

have given rise to smart tourism ecosystems—digitally interconnected environments in which hotels, travel agencies, online platforms and technology providers coordinate their activities through intelligent systems and real-time, data-driven decision-making (Gretzel et al., 2015). Within such ecosystems, knowledge, rather than physical or financial capital, has become the most strategically consequential organisational resource, and the capacity to create, share and apply it is widely regarded as the ultimate basis of competitive advantage and long-term sustainability (Grant, 1996; Alavi & Leidner, 2001). The central managerial problem is therefore no longer whether to adopt intelligent technologies, but how to convert the resources they generate into knowledge that is actually used in decisions and service delivery.

Three intelligent enablers are especially salient in this transformation: intelligent capability, intelligent infrastructure and intelligent trust. Intelligent capability refers to an organisation's ability to mobilise intelligent technologies, analytical resources and digital competencies to support adaptive learning and knowledge-driven action (Mikalef et al., 2020). Intelligent infrastructure denotes the integrated technological base—cloud platforms, AI applications, IoT networks and analytics tools—that enables connectivity and the flow of data across organisational boundaries (Bharadwaj, 2000; Li et al., 2022). Intelligent trust captures employees' confidence in the reliability, transparency, security and fairness of algorithmic and data-driven systems (Glikson & Woolley, 2020; Kluiters et al., 2023). Although these enablers are frequently discussed together, they are conceptually distinct: one is a competence, one is a technological endowment, and one is a psychological state, and there is little reason to assume that they shape knowledge processes in the same way or to the same degree.

Despite rising investment in these enablers, smart tourism organisations continue to struggle to translate intelligent resources into tangible knowledge-application outcomes (Pencarelli, 2020). The Knowledge-Based View (KBV) offers a compelling explanation: intelligent resources create value not in and of themselves, but only when they are activated through collaborative knowledge processes—above all, knowledge

sharing (Grant, 1996; Wang & Noe, 2010). Where sharing mechanisms are weak, even sophisticated technologies remain under-exploited, knowledge stays trapped in functional or individual silos, and decision-making fails to draw on the organisation's collective intelligence (Obrenovic et al., 2020). This reasoning implies that the effect of intelligent enablers on knowledge application is likely to be indirect, operating substantially through the degree to which knowledge is exchanged and recombined among employees—a mechanism that has rarely been modelled explicitly in the smart tourism context.

Against this backdrop, three gaps constrain current understanding. First, much of the existing research treats intelligent enablers as a single, undifferentiated construct, collapsing the technological, behavioural and psychological facets of digital transformation into one broad notion of 'intelligence' and thereby obscuring which facet actually drives knowledge outcomes (Mikalef et al., 2020; Atobishi et al., 2024). Studies rarely separate intelligent trust, intelligent infrastructure and intelligent capability, or compare their relative influence, even though a competence, an infrastructure and a state of confidence are theoretically expected to affect knowledge sharing through different pathways. Second, prior work has concentrated on direct technology–performance relationships and has paid limited empirical attention to the mechanism through which intelligent resources are converted into organisational knowledge; the mediating role of knowledge sharing as the process that links enablers to application remains under-investigated (Kmieciak, 2021; Le & Le, 2023). Third, the evidence base is dominated by developed economies, whereas developing economies—where digital maturity, organisational readiness and trust dynamics differ markedly—are strikingly under-represented, and smart tourism organisations in such settings have seldom been examined (Pencarelli, 2020; Atobishi et al., 2024). Jordan is a revealing setting in which to address these gaps: it is pursuing an ambitious digital-economy agenda under Vision 2030, while tourism contributes approximately 14% of GDP, making the sector both economically pivotal and digitally transitional.

To address these gaps, this study integrates

intelligent trust, intelligent infrastructure and intelligent capability within a single mediation model grounded in the KBV and Dynamic Capabilities Theory, and tests it among smart tourism organisations in Jordan. Rather than assuming that intelligent resources influence knowledge application directly, the model positions knowledge sharing as the pivotal mechanism through which the three enablers are translated into applied knowledge. Three research questions guide the investigation:

RQ1. To what extent do intelligent trust, intelligent infrastructure and intelligent capability influence knowledge sharing in smart tourism organisations?

RQ2. Does knowledge sharing mediate the relationship between each intelligent enabler and knowledge application?

RQ3. Which intelligent enabler exerts the strongest influence on knowledge outcomes, and what are the implications for tourism organisations in developing economies?

The study offers three contributions. Theoretically, it extends the KBV by demonstrating that intelligent enablers function as upstream antecedents of knowledge-based processes only when they are activated through collaborative sharing, thereby specifying a knowledge-mobilisation pathway that has remained largely implicit in prior work. Methodologically, it develops and empirically validates a multidimensional operationalisation of intelligent enablers tailored to the tourism context, enabling their distinct effects to be estimated rather than assumed. Practically, it provides decision-makers and policymakers in developing economies with an evidence-based basis for prioritising investment across capability, infrastructure and trust according to their actual contribution to knowledge outcomes.

The remainder of the paper is organised as follows. Section 2 develops the theoretical background and hypotheses. Section 3 describes the research methodology. Section 4 presents the empirical results. Section 5 discusses the findings and their theoretical and practical implications. Section 6 concludes and outlines the study's limitations and directions for future research.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Theoretical Foundation: The Knowledge-Based

View and Dynamic Capabilities

The study is grounded in the Knowledge-Based View (KBV) and Dynamic Capabilities Theory, two complementary perspectives on how organisations generate value from knowledge. Extending the resource-based view, the KBV treats knowledge as the most strategically important organisational asset and the principal source of sustainable competitive advantage (Grant, 1996; Alavi & Leidner, 2001). Crucially, it holds that performance depends not merely on possessing knowledge but on the firm's capacity to integrate, share and apply it across functional boundaries (Wang & Noe, 2010); knowledge that is held but not mobilised confers little advantage. Dynamic Capabilities Theory complements this view by emphasising the firm's ability to sense environmental change, seize emerging opportunities and reconfigure its resource base accordingly (Teece, 2007). Read together, the two theories imply that intelligent technologies become valuable only when embedded in organisational competencies and processes that continuously mobilise knowledge—the proposition that frames the present conceptualisation of intelligent enablers and knowledge processes. Accordingly, the KBV informs the study's treatment of knowledge sharing and application as the processes that convert resources into outcomes, while Dynamic Capabilities Theory underpins the treatment of intelligent capability as an adaptive, reconfiguring competence.

2.2 Smart Tourism Ecosystems and Intelligent Systems

Smart tourism ecosystems are technology-intensive environments in which tourists, hotels, travel agencies, platforms and service providers interact through intelligent systems built on AI, machine learning, IoT, big-data analytics and cloud computing (Gretzel et al., 2015). Unlike conventional tourism settings, these ecosystems depend on continuous digital connectivity, inter-organisational data exchange and real-time decision support to deliver personalised experiences and operational agility (Buhalis & Sinarta, 2019). In such contexts, intelligent systems do more than automate operations: they reshape how learning, collaboration and knowledge use unfold across the organisation, embedding data-driven routines into everyday service delivery. This makes smart tourism a particularly appropriate

setting in which to examine how intelligent enablers translate into knowledge processes, because the exchange and application of timely knowledge are inseparable from the quality of the services these organisations provide.

2.3 Intelligent Trust

Intelligent trust is defined as the extent to which employees are confident that intelligent technologies, digital platforms and data-driven systems are reliable, transparent, secure and fair (Glikson & Woolley, 2020; Kluiters et al., 2023). It is fundamentally a psychological state, and it differs from interpersonal trust in being socio-technical: its referents are algorithms, AI applications and data-governance regimes rather than colleagues, even though these systems increasingly mediate organisational communication. Theoretically, intelligent trust operates as an enabling condition that governs employees' willingness to engage with intelligent systems: higher trust lowers perceived technological risk and concerns about data misuse, which increases engagement with digital platforms and the willingness to contribute knowledge through them (Mubarak & Petraite, 2020; Brockman et al., 2018). Its organisational function is thus to reduce the perceived hazard of disclosure, making it a psychological prerequisite for knowledge sharing in smart tourism ecosystems where real-time data exchange is pervasive. What distinguishes intelligent trust from the other two enablers is that it neither performs work nor supplies technical means; it removes a barrier, and is therefore expected to influence knowledge sharing by permitting rather than propelling it.

2.4 Intelligent Infrastructure

Intelligent infrastructure refers to the integrated technological base through which data and knowledge are produced, processed, transmitted and used in digitally enabled environments (Bharadwaj, 2000; Li et al., 2022). It comprises cloud platforms, AI applications, IoT networks, big-data analytics, cyber-security systems and communication networks that jointly support organisational intelligence and integration. Its theoretical role is that of an enabling technological endowment: rather than a neutral conduit, infrastructure acts as an active broker that shapes how knowledge is codified, retrieved and co-created (Haffke et al., 2017). Organisationally, it

functions to connect dispersed units and external partners in real time, shorten learning cycles and support service innovation; in smart tourism specifically, it integrates customer data, service flows and operational information, easing communication bottlenecks and improving information transparency (Gupta et al., 2025). Intelligent infrastructure is distinct from intelligent trust in being a material, technical capacity rather than a psychological state, and distinct from intelligent capability in that it constitutes the tools and platforms available to the organisation rather than the human competence to exploit them. It is therefore expected to influence knowledge sharing by providing the channels through which knowledge can flow—necessary, but not by itself sufficient.

2.5 Intelligent Capability

Intelligent capability denotes an organisation's ability to exploit intelligent technologies, analytical resources and digital competencies to achieve adaptive learning and knowledge-driven performance (Mikalef et al., 2020; Atobishi et al., 2024). Grounded in Dynamic Capabilities Theory, it extends beyond the ownership of technology to encompass employees' skills and knowledge, their analytical proficiency, and the organisation's capacity to sense, integrate, share, learn and apply knowledge in dynamic environments. Its theoretical role is that of a higher-order, reconfiguring competence that determines how effectively the other resources are put to use; its organisational function is to convert raw data into actionable knowledge, personalise services, anticipate customer needs and resolve problems across functional boundaries (Awan et al., 2021; Kastelli et al., 2024). Intelligent capability is unique among the three enablers in being an enacted human-and-organisational competence rather than an artefact or an attitude: whereas infrastructure supplies the means and trust grants the permission, capability supplies the ability to act. Because collaborative knowledge behaviour depends most directly on employees who can interpret, combine and apply data-driven insight, intelligent capability is expected to exert the strongest influence on knowledge sharing of the three enablers.

Conceptual distinctions among the three intelligent enablers

Dimension of comparison	Intelligent Trust	Intelligent Infrastructure	Intelligent Capability
Conceptual definition	Employees' confidence that AI and data-driven systems are reliable, transparent, secure and fair	The integrated technological base (cloud, AI, IoT, analytics) enabling data flow and connectivity	The organisation's ability to exploit intelligent technologies and analytical competencies for adaptive, knowledge-driven action
Nature of the construct	Psychological / attitudinal state	Technological endowment / material resource	Enacted human-and-organisational competence
Primary theoretical anchor	KBV; trust in socio-technical systems	KBV; IT-capability perspective	Dynamic Capabilities Theory
Organisational function	Lowers the perceived risk of disclosure	Provides the channels for codifying, transmitting and retrieving knowledge	Provides the ability to interpret, combine and apply knowledge
Primary role toward knowledge sharing	Permits sharing (removes barriers)	Enables sharing (supplies the means)	Drives sharing (supplies the ability)
Expected relative effect on knowledge sharing	Positive, comparatively weaker (enabling / hygiene condition)	Positive, moderate (necessary but not sufficient)	Positive, strongest (most directly tied to collaborative behaviour)

2.6 Knowledge Sharing

Knowledge sharing is the process through which individuals, groups and organisational units exchange information, experience, insight and tacit understanding in order to improve collective performance (Wang & Noe, 2010). As one of the core knowledge-management activities, it conveys both explicit and tacit knowledge within and beyond the organisation (Obrenovic et al., 2020). Intelligent platforms and digital collaboration tools have greatly expanded the scale, speed and reach of sharing, enabling distributed work settings in which knowledge circulates in real time, learning is interactive, and problems are solved collaboratively (Gupta et al., 2025). In smart tourism, knowledge sharing is the mechanism that turns intelligent resources into coordinated decision-making, service personalisation and innovation, making it the natural candidate for the process that links intelligent enablers to knowledge application.

2.7 Knowledge Application

Knowledge application refers to the process of embedding acquired and shared knowledge into operational routines, strategic decisions, problem-solving and service improvement (Alavi & Leidner, 2001). It represents the point at which organisational knowledge is converted into

measurable outcomes—performance gains, innovation and competitive advantage—and, from a strategic standpoint, it is the application of knowledge rather than its mere possession that ultimately matters. Organisations that apply their collective knowledge effectively tend to be more innovative, more adaptive and, in consequence, more competitive in dynamic, knowledge-intensive digital environments (Kumar, 2024). Knowledge application therefore serves as the ultimate dependent construct in this study, with knowledge sharing as its proximate antecedent.

2.8 Hypothesis Development

2.8.1 Intelligent Trust and Knowledge Sharing

Within intelligent organisational settings, trust shapes knowledge-sharing behaviour by lowering risk perception and fostering a psychologically safe environment for disclosure. Because intelligent trust concerns confidence in algorithmic decision-making, data governance and system reliability rather than confidence in particular individuals (Glikson & Woolley, 2020), it is the form of trust most relevant to socio-technical exchange, where knowledge increasingly moves through digital rather than face-to-face channels. Employees who perceive intelligent platforms as transparent, fair and secure are more willing to contribute ideas, externalise tacit knowledge and participate in

collaborative knowledge behaviours (Brockman et al., 2018; Kmiecik, 2021). Conversely, low intelligent trust heightens concerns about data misuse, loss of ownership and algorithmic bias, and suppresses sharing. Some evidence cautions that trust may act more as a baseline condition than a strong driver—its absence obstructs sharing more than its presence propels it—yet, on balance and in KBV terms, intelligent trust is the psychological precondition that allows organisational knowledge stocks to flow through digital infrastructures. Accordingly:

H1. *Intelligent trust positively influences knowledge sharing in smart tourism organisations.*

2.8.2 Intelligent Infrastructure and Knowledge Sharing

Intelligent infrastructure provides the technological architecture on which knowledge-sharing processes are executed. Cloud platforms, AI-driven analytics, IoT devices and collaborative digital workspaces enable the communication, codification and retrieval of knowledge across time and space (Bharadwaj, 2000; Li et al., 2022). From a socio-technical perspective, infrastructure is not merely a passive channel but an active influence on how knowledge is produced, transmitted and re-used (Haffke et al., 2017). In tourism, intelligent infrastructure integrates customer data, service flows and operational information, reducing communication bottlenecks and improving information transparency (Gupta et al., 2025). The more advanced an organisation's intelligent infrastructure, the more it lowers the cost and friction of exchange and the more conducive it becomes to knowledge-sharing practices—although, consistent with Dynamic Capabilities reasoning, the availability of channels does not by itself guarantee their skilful use. Therefore:

H2. *Intelligent infrastructure positively influences knowledge sharing in smart tourism organisations.*

2.8.3 Intelligent Capability and Knowledge Sharing

Intelligent capability reflects an organisation's ability to deploy intelligent technologies effectively for knowledge processes. Grounded in Dynamic Capabilities Theory, it captures the firm's capacity to sense, absorb and apply knowledge in rapidly changing environments (Teece, 2007; Mikalef et al., 2020). Organisations with stronger intelligent capability are better able to identify valuable

knowledge, integrate it into existing routines and convert it into actionable insight, thereby stimulating both intra- and inter-unit knowledge flows (Kastelli et al., 2024). Capability also enhances employees' ability to engage meaningfully with intelligent systems, interpret data-driven insight and participate in collaborative problem-solving (Awan et al., 2021). Because it directly determines whether the means supplied by infrastructure and the permission granted by trust are actually translated into collaborative action, intelligent capability is expected to be the most proximate driver of knowledge sharing; in smart tourism organisations, this manifests as adaptive service delivery and a stronger culture of knowledge exchange. Accordingly:

H3. *Intelligent capability positively influences knowledge sharing in smart tourism organisations.*

2.8.4 Knowledge Sharing as a Mediator

From a KBV standpoint, intelligent enablers become strategically valuable only when they are converted into collective knowledge action. Intelligent trust, infrastructure and capability establish the conditions for knowledge processes, but their influence on knowledge application is expected to operate largely through the active circulation, recombination and integration of knowledge across the organisation (Wang & Noe, 2010; Le & Le, 2023). Knowledge sharing is the connective process that delivers knowledge to the right actors at the right time, supports collective learning, and informs decision-making and service design (Obrenovic et al., 2020). In smart tourism, where service quality and customer experience depend on timely and accurate information, knowledge sharing is therefore expected to mediate the relationship between each intelligent enabler and knowledge application. Accordingly:

H4. *Knowledge sharing mediates the relationship between intelligent trust and knowledge application.*

H5. *Knowledge sharing mediates the relationship between intelligent infrastructure and knowledge application.*

H6. *Knowledge sharing mediates the relationship between intelligent capability and knowledge application.*

Figure 1 presents the proposed conceptual model integrating these relationships.

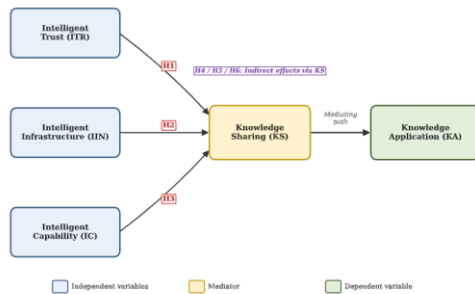


Figure 1: Proposed Conceptual Research Model

3. METHODOLOGY

3.1 Research Design

This study adopted a cross-sectional quantitative design to test the proposed model. A quantitative approach was selected because it permits the statistical assessment of latent constructs and complex multivariate relationships, including mediation effects (Hair et al., 2022). The cross-sectional design was deemed appropriate given the study's objective of capturing employees' perceptions of intelligent enablers and knowledge processes at a particular phase of digital transformation in Jordan's smart tourism sector.

3.2 Sample and Data Collection

The target population comprised employees of smart tourism organisations in Jordan, including luxury hotels, travel agencies, online tourism platforms and tourism technology service providers. These organisations were selected because they typically operate the most digitally integrated systems and exhibit relatively higher levels of intelligent-system adoption within the Jordanian tourism sector.

Because no comprehensive sampling frame of employees in digitally mature tourism organisations was available, non-probability convenience sampling was employed, as is common in organisational research dealing with technologically advanced settings (Bihu, 2021). To mitigate the limitations of convenience sampling, participation was sought across multiple sub-sectors and organisation sizes, and the survey was disseminated through professional networks and organisational mailing lists rather than a single channel.

The required sample size was estimated using G*Power 3.1 for a multiple-regression model with three predictors, an anticipated medium effect

size ($f^2 = 0.15$), statistical power of 0.95 and $\alpha = 0.05$, yielding a minimum of 119 cases. To meet the more conservative requirements of PLS-SEM (Hair et al., 2022) and to allow for reliable bootstrapping, a substantially larger sample was targeted. A total of 312 questionnaires were distributed online; after removing incomplete and inattentive responses, 285 valid responses were retained for analysis, representing a 91.3% usable response rate.

3.3 Measurement Instrument

All constructs were measured using multi-item reflective scales adapted from validated prior studies and refined for the smart tourism context. Intelligent trust was measured with five items adapted from Glikson and Woolley (2020) and Kluiters et al. (2023). The five items were adapted from Bharadwaj (2000) and Li et al. (2022) for the measurement of intelligent infrastructure. Five items were used to assess intelligent capability adapted from Mikalef et al., 2020 and Atobishi et al., 2024. Five items from Wang, & Noe (2010) and Obrenovic et al. (2020) were used to measure knowledge sharing. The measure of knowledge application was taken from Alavi and Leidner (2001) and Kumar (2024) comprising five items. Each question was measured using a 5 point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Four academic experts on knowledge management and digital transformation and three senior practitioners from the smart tourism sector in Jordan validated the content and contextual appropriateness of the instrument. To ensure preliminary reliability, a pilot study was conducted to test the reliability of the constructs with 30 respondents, where the Cronbach's alpha for each construct was above 0.80. Small changes to the wording were added in response to feedback from pilots.

3.4 Data Analysis

Data analysis followed a two-stage approach. Preliminary descriptive analyses, reliability tests, normality tests and exploratory factor analysis were conducted using IBM SPSS Statistics version 31. The measurement and structural models were then evaluated using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4, given its suitability for complex models, mediation testing and non-normal data

(Hair et al., 2022). Indirect effects were assessed using bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals (Hair et al., 2022; Preacher & Hayes, 2008).

3.5 Common Method Bias and Ethical Considerations

Several procedural and statistical remedies were applied to control for common method bias (CMB) (Podsakoff et al., 2003). Respondents were assured of anonymity and confidentiality, items were randomised within the questionnaire, and reverse-coded items were included. Harman's single-factor test was performed; the first extracted factor accounted for 55.14% of the variance, and four factors with eigenvalues above 1 emerged, indicating that CMB is unlikely to be a substantive concern (Podsakoff et al., 2003). Additionally, full collinearity VIFs were all below the threshold of 3.3 (Kock, 2015), providing further evidence against CMB.

The study was conducted in accordance with established ethical research standards. Participation was entirely voluntary, informed consent was obtained from all respondents and no personally identifying information was collected.

Table 1: Demographic characteristics of respondents (N = 285)

Variable	Category	Frequency	Percent (%)
Age	Below 25	15	5.4
	25–34	105	35.7
	35–44	82	29.3
	45–54	63	22.5
	55 and above	20	7.1
Gender	Female	82	27.5
	Male	189	67.5
	Prefer not to say	14	5
Education	Diploma	27	9.6
	Bachelor	96	34.3
	Master	118	42.1
	PhD	34	10.4
	Professional qualification	8	2.9
	Vocational training	2	0.7
Job role	Hotel manager/department head	78	27.9
	Operations/front-office manager	58	20.7

Data were stored on a password-protected device accessible only to the research team.

4. RESULTS

4.1 Sample Characteristics

The sample consisted of 285 employees in the smart tourism industry in Jordan. Most of the respondents were male (67.5%) while female respondents made up 27.5%. The respondents were relatively young with the majority (65.0%) between 25-44 years. The majority of respondents had a high level of education, with 86.8% having completed a bachelor's degree or higher and 42.1% a master's degree, reflecting the information-rich demands of digitally supported tourism careers. About 78.2% of the respondents had six years or more of professional experience and about 79.2% had four years or more of direct experience working with intelligent or digital systems. The distribution of the respondents was uniform among luxury hotels (37.5%), travel agencies (27.9%), tourism technology providers (15.0%), online platforms (14.6%) and other tourism services (5.0%). The demographic profile is detailed in Table 1.

Variable	Category	Frequency	Percent (%)
	Tourism services specialist	76	27.1
	Digital marketing/booking specialist	64	21.1
	Data/systems analyst	5	1.8
	Product/service coordinator	4	1.4
Experience (years)	Less than 2	21	7.5
	2–5	45	14.3
	6–10	97	34.6
	11–15	71	25.4
	More than 15	51	18.2
Sub-sector	Luxury hotels	110	37.5
	Travel agencies	78	27.9
	Online tourism platforms	41	14.6
	Tourism technology services	42	15
	Other tourism services	14	5
Organisation size	Small (1–49)	20	7.1
	Medium (50–249)	98	33.2
	Large (250+)	167	59.6
Experience with intelligent systems (years)	Less than 1	18	6.4
	1–3	45	14.3
	4–6	86	30.7
	7–10	88	31.4
	More than 10	48	17.1

4.2 Descriptive Statistics and Normality

The mean scores of the constructs were closer to the middle of the scales ($M \approx 2.94 - 3.08$), reflecting moderate agreement and suggesting that intelligent enablers and knowledge practices exist but have not yet been optimised in the organisations studied. Standard deviations were between 1.13 and 1.50, which indicates that there was a significant level of variance between organisations in terms of their digital maturity and knowledge culture. The skewness and kurtosis values were within ± 2 , Table 2: Descriptive statistics for measurement items

meeting the common rule of thumb for normality at the item level (Hair et al., 2019). As usual for Likert scale data, the Kolmogorov–Smirnov test showed that there were statistically significant deviations from a strict normal distribution ($p < 0.001$). Based on this, PLS SEM was chosen as the primary estimation method as it does not need multivariate normality (Hair et al., 2022). The descriptive statistics are provided in the following table (Table 2).

Construct	Item	Mean	SD	Skewness	Kurtosis
Intelligent Trust (ITR)	ITR1	3.01	1.14	-0.08	-0.81
	ITR2	2.99	1.15	-0.02	-0.82

Construct	Item	Mean	SD	Skewness	Kurtosis
	ITR3	3.00	1.14	-0.08	-0.81
	ITR4	3.02	1.13	-0.05	-0.79
	ITR5	2.99	1.15	-0.02	-0.82
Intelligent Infrastructure (IIN)	IIN1	3.02	1.18	-0.04	-0.74
	IIN2	3.01	1.14	0.00	-0.71
	IIN3	3.02	1.17	0.04	-0.76
	IIN4	3.07	1.13	-0.13	-0.67
	IIN5	3.00	1.14	-0.13	-0.65
Intelligent Capability (IC)	IC1	2.97	1.18	-0.11	-0.77
	IC2	2.95	1.19	-0.08	-0.88
	IC3	2.93	1.23	0.07	-0.96
	IC4	2.91	1.15	0.13	-0.64
	IC5	2.96	1.21	-0.02	-0.86
Knowledge Sharing (KS)	KS1	3.02	1.35	0.04	-1.16
	KS2	2.99	1.33	0.07	-1.10
	KS3	3.04	1.30	-0.03	-1.02
	KS4	3.02	1.36	-0.05	-1.23
	KS5	2.98	1.32	0.03	-1.10
Knowledge Application (KA)	KA1	3.13	1.48	-0.16	-1.34
	KA2	3.06	1.50	-0.08	-1.40
	KA3	3.08	1.48	-0.02	-1.38
	KA4	3.08	1.45	-0.12	-1.34
	KA5	3.06	1.50	-0.05	-1.44

Note: N = 285. SD = Standard deviation.

4.3 Sampling Adequacy

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.963, well above the 0.80 benchmark for ‘marvellous’ adequacy (Kaiser, 1974). Bartlett’s test of sphericity was significant

($\chi^2 = 7,088.349$, $df = 301$, $p < 0.001$), indicating sufficient inter-item correlations for factor analysis. These results, presented in Table 3, confirm the data’s suitability for both exploratory and confirmatory analyses.

Table 3: KMO and Bartlett’s test

Test	Measure	Value
Kaiser–Meyer–Olkin (KMO)	Sampling adequacy	0.963
Bartlett’s test of sphericity	Approx. Chi-Square	7,088.349
	df	301
	Sig.	< 0.001

4.4 Measurement Model

The measurement model was evaluated for

indicator reliability, internal consistency, convergent validity and discriminant validity. All

outer loadings exceeded the recommended threshold of 0.70 and ranged from 0.826 to 0.957, supporting indicator reliability (Hair et al., 2022). Cronbach's alpha values ranged from 0.906 to 0.971 and composite reliability (CR) values ranged from 0.930 to 0.978, both exceeding the 0.70 benchmark and confirming strong internal consistency.

Table 4: Outer loadings of measurement items

Construct	Item	Loading
Intelligent Trust	ITR1	0.845
	ITR2	0.880
	ITR3	0.881
	ITR4	0.889
	ITR5	0.886
Intelligent Infrastructure	IIN1	0.847
	IIN2	0.876
	IIN3	0.856
	IIN4	0.826
	IIN5	0.855
Intelligent Capability	IC1	0.862
	IC2	0.904
	IC3	0.884
	IC4	0.878
	IC5	0.888
Knowledge Sharing	KS1	0.913
	KS2	0.927
	KS3	0.928
	KS4	0.913
	KS5	0.912
Knowledge Application	KA1	0.944
	KA2	0.948
	KA3	0.957
	KA4	0.951
	KA5	0.942

Average Variance Extracted (AVE) values ranged from 0.726 to 0.897, exceeding the 0.50 cut-off and supporting convergent validity. Variance inflation factors (VIF) for all constructs were below 5, indicating no multicollinearity concerns (Hair et al., 2022). Outer loadings and reliability indicators are presented in Tables 4 and 5.

Table 5: Reliability and convergent validity

Construct	Items	Mean	SD	α	CR	AVE	VIF
Intelligent Trust (ITR)	5	3.00	1.01	0.925	0.943	0.768	1.586
Intelligent Infrastructure (IIN)	5	3.02	0.98	0.907	0.930	0.726	1.816

Construct	Items	Mean	SD	α	CR	AVE	VIF
Intelligent Capability (IC)	5	2.94	1.05	0.928	0.947	0.780	1.911
Knowledge Sharing (KS)	5	3.00	1.22	0.953	0.964	0.842	3.962
Knowledge Application (KA)	5	3.08	1.41	0.971	0.978	0.897	3.768

Note: α = Cronbach's alpha; CR = Composite reliability; AVE = Average Variance Extracted; VIF = Variance Inflation Factor.

4.5 Discriminant Validity

Discriminant validity was examined using the Fornell–Larcker criterion (Fornell & Larcker, 1981). As shown in Table 6, the square root of the AVE for each construct (on the diagonal) exceeded its correlations with all other constructs (off-Table 6: Discriminant validity (Fornell–Larcker criterion)

diagonal), confirming discriminant validity. Heterotrait–Monotrait (HTMT) ratios (Henseler et al., 2015) were additionally examined and all values were below the conservative 0.85 threshold, providing further support.

Construct	ITR	IIN	IC	KS	KA
Intelligent Trust (ITR)	0.876				
Intelligent Infrastructure (IIN)	0.441**	0.852			
Intelligent Capability (IC)	0.381**	0.499**	0.883		
Knowledge Sharing (KS)	0.581**	0.640**	0.665**	0.918	
Knowledge Application (KA)	0.574**	0.636**	0.650**	0.834**	0.948

Note: Diagonal values (in bold conceptually) represent the square root of AVE; off-diagonal values are construct correlations. ** $p < 0.01$.

4.6 Structural Model and Hypothesis Testing

Following confirmation of the measurement model, the structural model was assessed using path coefficients, t-statistics, effect sizes (f^2), coefficients of determination (R^2), adjusted R^2 , and predictive relevance (Q^2). The model explained 64.2% of the variance in knowledge sharing (adjusted $R^2 = 0.638$) and 73.9% in knowledge application (adjusted $R^2 = 0.735$), with Q^2 values of 0.643 and 0.740 respectively, indicating substantial predictive relevance (Hair et al., 2022).

As shown in Table 7, all three intelligent enablers exerted a positive and significant direct effect on

knowledge sharing. Intelligent capability was the strongest predictor ($\beta = 0.405$, $t = 7.23$, $p < 0.01$, $f^2 = 0.270$), followed by intelligent infrastructure ($\beta = 0.306$, $t = 5.37$, $p < 0.01$, $f^2 = 0.196$) and intelligent trust ($\beta = 0.300$, $t = 5.26$, $p < 0.01$, $f^2 = 0.176$). Knowledge sharing exerted a strong, positive effect on knowledge application ($\beta = 0.568$, $t = 10.52$, $p < 0.01$, $f^2 = 0.474$). The three enablers also exerted smaller but significant direct effects on knowledge application, supporting partial—rather than full—mediation. Hypotheses H1, H2 and H3 are therefore supported.

Path	β	SE	t-value	p	f^2	Decision
H1: ITR → KS	0.300	0.057	5.26	< 0.01	0.176	Supported
H2: IIN → KS	0.306	0.057	5.37	< 0.01	0.196	Supported
H3: IC → KS	0.405	0.056	7.23	< 0.01	0.270	Supported
ITR → KA	0.130	0.059	2.20	< 0.05	0.075	Significant
IIN → KA	0.145	0.058	2.50	< 0.05	0.082	Significant
IC → KA	0.153	0.057	2.68	< 0.01	0.090	Significant

Path	β	SE	t-value	p	f ²	Decision
KS → KA	0.568	0.054	10.52	< 0.01	0.474	Significant

Note: ITR = Intelligent Trust; IIN = Intelligent Infrastructure; IC = Intelligent Capability; KS = Knowledge Sharing; KA = Knowledge Application.

4.7 Mediation Analysis

Mediation was tested using bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals (Hair et al., 2022; Preacher & Hayes, 2008). As shown in Table 8, all three indirect effects through knowledge sharing were statistically significant and none of the confidence intervals included zero. The mediating effect of intelligent capability on knowledge application via knowledge sharing was the strongest (indirect β =

0.230), followed by intelligent infrastructure (indirect β = 0.174) and intelligent trust (indirect β = 0.170). Because the direct effects of the three enablers on knowledge application also remained significant, the mediation is partial. Hypotheses H4, H5 and H6 are therefore supported. These findings indicate that knowledge sharing is the principal mechanism through which intelligent enablers translate into enhanced knowledge application outcomes.

Table 8: Indirect (mediation) effects via knowledge sharing

Path	Indirect β	SE	t-value	95% (LL)	CI	95% (UL)	CI	Decision
H4: ITR → KS → KA	0.170	0.034	5.00	0.108		0.241		Supported (partial)
H5: IIN → KS → KA	0.174	0.035	4.97	0.111		0.249		Supported (partial)
H6: IC → KS → KA	0.230	0.036	6.39	0.164		0.305		Supported (partial)

Note: Bootstrapping with 5,000 resamples; bias-corrected 95% confidence intervals. LL = lower limit; UL = upper limit.

4.8 Coefficient of Determination and Predictive Relevance

The explanatory and predictive ability of the structural model is summarised in Table 9. In the context of PLS-SEM, these R² are significant with 64.2% of the variance in knowledge sharing and 73.9% in knowledge application being explained.

Table 9: R², adjusted R², and predictive relevance (Q²)

Construct	R ²	Adjusted R ²	Q ²
Knowledge Sharing	0.642	0.638	0.643
Knowledge Application	0.739	0.735	0.740

Confirmed by blindfolding, the Q² values for knowledge sharing and knowledge application were 0.643 and 0.740, respectively, which were both well above the value of zero, indicating a very good out-of-sample predictive relevance of the model.

4.9 Common Method Bias

Harman's single-factor test produced four factors with eigenvalues greater than 1; the first factor explained 55.14% of the variance, with the remaining variance distributed across additional factors (Table 10). Although this is close to the 50% threshold sometimes cited, it does not constitute

conclusive evidence of CMB, particularly in light of the procedural controls applied, the full collinearity VIFs all being below 3.3 (Kock, 2015), and the strong discriminant validity observed. CMB is therefore unlikely to be a substantive threat to the validity of the findings.

Table 10: Harman's single-factor test (total variance explained)

Component	Eigenvalue	% of Variance	Cumulative %
1	13.785	55.136	55.136
2	2.437	9.746	64.882
3	1.861	7.443	72.323
4	1.345	5.378	77.701

Note: Extraction method = Principal Component Analysis.

5. DISCUSSION

5.1 Overview of Findings

This study set out to examine how three intelligent enablers—intelligent trust, intelligent infrastructure and intelligent capability—affect knowledge application in Jordanian smart tourism organisations, and whether knowledge sharing mediates these relationships. The results support all six hypotheses and reveal a consistent pattern: each intelligent enabler exerts a significant positive effect on knowledge sharing, knowledge sharing in turn strongly influences knowledge application, and the impact of the enablers on knowledge application is transmitted mainly—though not exclusively—through knowledge sharing. Taken together, the findings indicate that intelligent resources shape applied knowledge less by direct technological effect than by fostering the collaborative processes through which knowledge is mobilised, a result examined enabler by enabler below.

5.2 Intelligent Capability as the Strongest Predictor

Intelligent capability emerged as the strongest predictor of knowledge sharing ($\beta = 0.405$). This finding is consistent with evidence that it is digital and analytical competencies—rather than the technologies themselves—that transform data into actionable insight (Mikalef et al., 2020; Awan et al., 2021; Kastelli et al., 2024), and it aligns with Dynamic Capabilities Theory, which locates competitive advantage in turbulent markets in the capacity to sense, learn and reconfigure (Teece, 2007). The result can be explained by the nature of capability itself: because it is an enacted human-and-organisational competence, it acts on knowledge sharing more directly than an endowment or an attitude can, determining whether the means and permissions supplied by infrastructure and trust are actually put to collaborative use. For smart tourism organisations in Jordan, this implies that human-centred

competencies such as data literacy, analytical reasoning and adaptive learning are more decisive for collaborative knowledge behaviour than the mere presence of intelligent systems.

5.3 The Role of Intelligent Infrastructure

Intelligent infrastructure was significantly and positively associated with knowledge sharing ($\beta = 0.306$), confirming its role in supporting the connectivity, codification and retrieval of knowledge (Bharadwaj, 2000; Li et al., 2022). Its effect was nonetheless weaker than that of intelligent capability, a gap that admits a socio-technical explanation: well-developed digital platforms supply the channels for exchange but cannot substitute for the human competencies required to exploit them (Haffke et al., 2017). In other words, infrastructure is necessary but not sufficient—it enables sharing without guaranteeing it. This pattern cautions against a common tendency to over-invest in technological hardware and platforms without commensurate investment in the digital skills and learning systems needed to activate them.

5.4 The Role of Intelligent Trust

Intelligent trust also had a positive effect on knowledge sharing, but the smallest of the three ($\beta = 0.300$). This is consistent with research showing that greater confidence in algorithmic decision-making, data governance and system fairness reduces the perceived risk of disclosure (Glikson & Woolley, 2020; Kmiecik, 2021; Kluiters et al., 2023). The comparatively modest—though still meaningful—effect suggests that, in Jordan's smart tourism sector, intelligent trust currently behaves more as a hygiene factor than as a primary driver: its absence obstructs sharing, whereas its presence must be complemented by capability and infrastructure to activate knowledge processes fully. This interpretation is congruent with the view of trust as an enabling condition that grants permission to share rather than a force that

propels sharing on its own.

5.5 Knowledge Sharing as the Pivotal Mechanism

Knowledge sharing exhibited the strongest direct effect in the model ($\beta = 0.568$ on knowledge application) and mediated every relationship between the intelligent enablers and knowledge application. The mediation was partial, since the direct effects of the three enablers on knowledge application remained significant. This pattern echoes Le and Le (2023) and Kmieciak (2021), who position knowledge sharing as the integrative mechanism that converts organisational and technological resources into knowledge outcomes. The result reinforces the study's central argument: intelligent enablers matter, but they deliver applied knowledge chiefly when the knowledge they generate is shared, combined and synthesised through collaborative work, rather than through the possession of technology as such.

5.6 Theoretical Contributions

The study makes three theoretical contributions. First, it extends the KBV by demonstrating that intelligent enablers operate as upstream antecedents of knowledge-based competitive advantage only when they are converted into knowledge processes through collaborative sharing. This enriches the foundational accounts of Grant (1996) and Alavi and Leidner (2001) by introducing an additional, digitally mediated layer of knowledge antecedents—intelligent enablers—positioned upstream of the sharing and application processes on which those accounts focus.

Second, the study advances the intelligent-enablers literature by disaggregating what is often treated as a single construct into three distinct enablers—intelligent trust, intelligent infrastructure and intelligent capability—and demonstrating that they influence knowledge sharing to different degrees. The finding that infrastructure matters less than capability, and that trust functions largely as an enabling condition, indicates that research on digital transformation should attend to the human-centred and socio-technical facets of intelligence rather than treating it as a monolithic, purely technological construct (Mikalef et al., 2020; Atobishi et al., 2024).

Third, the study extends the empirical reach of this literature to a smart tourism context in a developing economy, in contrast to the developed-market settings that dominate prior research, thereby responding to calls for context-sensitive

evidence on digital transformation (Pencarelli, 2020). In doing so, it shows that the mechanisms linking intelligent resources to knowledge outcomes hold in a transitional digital economy, while also revealing a distinctive emphasis on human capability that may be characteristic of such settings.

5.7 Practical Implications

The findings translate into targeted guidance for several stakeholder groups. For tourism managers, the clear priority is to invest in intelligent capability—through digital-training programmes, analytics literacy and adaptive-learning platforms—because it is the competence to use intelligent technologies, more than their presence, that drives collaborative knowledge behaviour and, ultimately, knowledge application. Managers should treat capability-building not as a one-off training expense but as a continuous programme that pairs every technology roll-out with the skills required to exploit it.

For digital-transformation leaders, the results argue for sequencing and balance: infrastructure investment should proceed hand in hand with capability development, since platforms that are not matched by skills tend to be under-used. Leaders should also institutionalise trust as a design principle—embedding transparent data governance, explainable AI practices and visible cybersecurity safeguards—so that employees feel safe contributing knowledge through intelligent systems rather than withholding it.

For technology providers serving the tourism sector, the evidence suggests that value is realised not by supplying ever more sophisticated tools alone, but by bundling platforms with training, onboarding and usability features that lower the competence threshold for effective use. Solutions that make analytical insight interpretable to non-specialist tourism staff are likely to generate greater knowledge-sharing returns than technically advanced systems offered without such support.

For policymakers in Jordan and comparable developing economies, the findings imply that digital-transformation strategy should combine infrastructure investment with large-scale upskilling and with regulation that fosters trust in data-driven systems; strategies that emphasise technology alone risk neglecting the human and behavioural levers through which smart

investments yield returns. For Jordanian tourism authorities specifically, aligning sector initiatives with the Vision 2030 digital agenda—by funding data-literacy and analytics training across hotels, agencies and platforms, and by promoting common standards for data governance and security—would help convert the sector's substantial technology investments into applied knowledge, service quality and competitiveness.

6. CONCLUSION

This study examined how intelligent enablers shape knowledge application in Jordanian smart tourism organisations and established knowledge sharing as the pivotal mechanism through which these enablers add organisational value. The findings show that intelligent capability is the most influential enabler of knowledge sharing, followed by intelligent infrastructure and intelligent trust, and that knowledge sharing partially mediates the relationship between each enabler and knowledge application. The model explains a substantial share of the variance in both knowledge sharing (64.2%) and knowledge application (73.9%), attesting to its explanatory and predictive strength. By integrating three distinct intelligent enablers within a KBV- and dynamic-capabilities-based framework and testing it in a developing-economy smart tourism setting, the study offers both theoretical refinement and practical guidance for the digital transformation of tourism organisations.

6.1. Limitations

Several limitations should be acknowledged. First, the cross-sectional design precludes strong causal inference; although the hypothesised directions are grounded in theory and prior evidence, they require confirmation through longitudinal designs that can establish temporal precedence. Second, the data were drawn exclusively from self-reported employee perceptions collected from a single source, and while procedural and statistical remedies were applied, only a genuinely multi-source design incorporating objective indicators could fully rule out common-method bias. Third, the constructs capture perceptions of intelligent technologies that are themselves evolving rapidly, so the meaning and salience of intelligent trust, infrastructure and capability may shift as the underlying technologies mature. Fourth, the study relies on perceptual measures of knowledge application and lacks objective organisational-

performance indicators. Fifth, the evidence is contextually specific to Jordan's smart tourism sector, whose digital maturity and trust dynamics may differ from those of other sectors or countries, limiting generalisability. Finally, because no comprehensive sampling frame existed, convenience sampling was used; although appropriate under these conditions, it may introduce selection biases that probability-based sampling would avoid.

6.2 Future Research

These limitations open several promising research avenues. Longitudinal and time-lagged designs would help establish the causal ordering among intelligent enablers, knowledge sharing and knowledge application, while multi-source and multi-method designs—combining employee perceptions with objective organisational-performance data—would strengthen causal inference and mitigate common-method concerns. Cross-country and cross-industry comparisons would clarify the generalisability of the model across settings of differing digital maturity. Future work could also extend the framework to emerging phenomena reshaping digitally mediated knowledge work, including generative AI and its effect on knowledge creation and sharing, AI governance and explainable AI as antecedents of intelligent trust, human-AI collaboration as a new locus of capability, and knowledge analytics, digital twins and digital ecosystems as infrastructures for knowledge mobilisation. Finally, incorporating moderators such as digital leadership, organisational culture, employee engagement and technological readiness, and additional outcomes such as innovation performance, service quality and customer-experience indices, would deepen understanding of how—and under what conditions—intelligent resources are converted into applied knowledge.

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