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Personalized Classification Models for Service Systems: Algorithmic Commonality between Tourist Profiling and Patient Stratification

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Abstract

This study proposes a unified framework of personalized classification models for intelligent service systems by comparing tourist profiling in smart tourism with patient stratification in healthcare management. Rather than treating personalization as a domain-specific or medical innovation, the paper conceptualizes it as a service system and management science problem centered on classification-driven decision support. The analysis demonstrates that both tourism and healthcare rely on the same functional logic of personalization, including user segmentation, behavior prediction, recommendation, adaptive service design, and feedback-based learning. These shared functions reveal an algorithmic and governance equivalence between tourist personas and patient subtypes, as well as between itinerary recommendation and care pathway design. By shifting the evaluation of personalization from technical accuracy to service outcomes such as relevance, efficiency, transparency, and trust, the study highlights the managerial value of classification models in complex service environments. The findings confirm that personalization is a transferable service system methodology rather than a sector-specific technique. Tourism is identified as the methodological origin of many personalization practices, while healthcare serves as a high-stakes application context. This cross-domain perspective advances understanding of how AI-enabled classification supports intelligent services and institutional decision-making.

Keywords

Personalized Classification; Service Systems; Tourist Profiling; Patient Stratification; Intelligent Services; Decision Support; Cross-Domain Methodology

1. Introduction: Personalization as a Service System Problem

Personalization has emerged as a defining feature of contemporary service systems, reshaping how organizations design, deliver, and evaluate services. In both tourism and healthcare, personalization is often framed as a domain-specific technical

achievement-tourist recommendation systems on the one hand and patient stratification models on the other. This study adopts a different positioning: personalization is fundamentally a service science and management problem rather than a medical or technological one. Its core function is to enable intelligent service systems to classify users, anticipate needs, and customize service pathways under conditions of uncertainty and resource constraints.

Service research has long emphasized that value is co-created through interactions between providers and users rather than embedded in products alone (Vargo & Lusch, 2004). Within this logic, personalization represents a managerial strategy for aligning service offerings with heterogeneous user preferences and needs. Tourism platforms segment visitors into personas to design itineraries, pricing strategies, and experiences. Healthcare systems stratify patients into subtypes to allocate care resources and design treatment pathways. Despite differences in domain content, both systems rely on the same methodological foundation: classification-driven personalization.

The core argument of this paper is that tourism and healthcare share a common personalization architecture based on four interrelated functions: user segmentation, behavior prediction, risk or need classification, and service customization. First, user segmentation groups individuals into meaningful categories. In tourism, this produces tourist personas such as cultural explorers or leisure seekers. In healthcare, it produces patient cohorts based on risk profiles or disease subtypes. Second, behavior prediction anticipates future actions or needs, such as travel intent or disease progression. Third, classification translates complex data into actionable categories that guide decisions. Finally, service customization tailors experiences or care pathways to these categories.

This functional equivalence reveals a deeper methodological isomorphism. Tourist personas are structurally equivalent to patient subtypes, both serving as classification outputs that simplify complexity and enable targeted service design. Similarly, recommendation systems in tourism correspond to care pathway design in healthcare, and experience optimization parallels outcome optimization. These parallels suggest that personalization should be analyzed through the lens of intelligent service systems rather than through isolated sectoral perspectives.

Recommender systems research demonstrates that personalization depends on predictive classification models that infer preferences and needs from heterogeneous data sources (Adomavicius & Tuzhilin, 2005). In smart tourism, these models integrate mobility traces, booking histories, and user-generated content to construct tourist profiles and recommend services (Gretzel et al., 2015). In healthcare, algorithmic stratification integrates clinical, demographic, and behavioral data to categorize patients and guide resource allocation (Obermeyer et al., 2019). In both cases, classification models function as decision support mechanisms that structure how services are delivered.

Importantly, personalization also reflects core service quality principles. Parasuraman, Zeithaml, and Berry (1988) argue that perceived service quality depends on reliability, responsiveness, and empathy-dimensions that are operationalized in digital environments through personalized interactions. Whether through customized travel itineraries or adaptive care plans, classification-based personalization directly influences user satisfaction and trust. Thus, performance cannot be evaluated solely by technical accuracy but must be assessed in terms of service relevance, experience quality, and institutional legitimacy.

This perspective motivates three research questions.

RQ1: What algorithmic structures are shared by tourist profiling and patient stratification? This question investigates whether similar classification logics and model architectures underpin personalization across domains.

RQ2: How do classification models enable personalized service decisions? Here, the focus is on the decision functions of classification, such as segmentation, prediction, and recommendation, rather than on specific algorithms.

RQ3: How can performance be evaluated beyond technical accuracy? This question shifts attention from predictive metrics to service-oriented criteria, including user satisfaction, efficiency, transparency, and trust.

By framing personalization as a service system problem, this study contributes to management science in three ways. First, it unifies tourism and healthcare under a common conceptual framework of intelligent service classification. Second, it redefines patient stratification as a form of personalized service design rather than as a purely medical activity. Third, it advances evaluation criteria that emphasize service and governance outcomes over algorithmic performance alone.

Tourism and healthcare are therefore treated not as separate analytical worlds but as parallel laboratories for studying personalized classification in complex service systems. Tourism provides the methodological origin of personalization practices through recommendation and experience design, while healthcare represents a high-stakes application context where similar models are used for risk and need stratification. Together, they demonstrate that personalization is a transferable management methodology grounded in classification-driven service logic rather than domain-specific knowledge.

2. Theoretical Foundations: Personalization in Intelligent Service Systems

Personalization in intelligent service systems is grounded in several complementary theoretical traditions that explain how classification and prediction enable customized service delivery. These foundations include service-dominant logic, the experience economy, personalization theory, predictive classification, and decision support systems (DSS). Together, they establish personalization as a managerial and service science mechanism, rather than a domain-specific technical achievement.

2.1. Service-Dominant Logic and Experience Economy

Service-dominant logic conceptualizes value as co-created through interactions between providers and users, mediated by information and institutional arrangements (Lusch & Nambisan, 2015). Within this framework, personalization is not an optional enhancement but a core strategy for aligning services with heterogeneous user needs. Tourism platforms personalize itineraries and experiences, while healthcare systems personalize care pathways and risk management strategies. Both domains rely on classification to structure these interactions.

The experience economy further emphasizes that modern services compete on the basis of differentiated and memorable experiences rather than standardized outputs (Pine & Gilmore, 1999). This personalized classification logic is highly transferable to cultural heritage services, such as the digital profiling and experience design for Huidong Intangible Cultural Heritage platforms. By classifying visitors based on their cultural affinity and engagement history, intelligent systems can dynamically customize exhibition pathways and heritage learning experiences. In tourism, experience design is explicit through curated journeys and themed destinations. In healthcare, experience manifests through continuity of care and patient-centered pathways. Personalized classification models operationalize this logic by grouping users into segments that can receive tailored experiences or interventions.

2.2. Personalization Theory and Predictive Classification

Personalization theory focuses on adapting services based on inferred user preferences, contexts, and future behaviors. Wedel and Kannan (2016) argue that data-driven personalization integrates segmentation, targeting, and real-time adaptation into a unified decision framework. Classification models are the analytical core of this framework, transforming raw data into user profiles that support differentiated service actions.

Predictive classification provides the methodological basis for personalization. Hastie, Tibshirani, and Friedman (2009) demonstrate that classification models reduce complex, high-dimensional data into categorical structures that guide decision-making. In tourism, these categories correspond to tourist personas or travel intentions. In healthcare, they correspond to patient subtypes or risk groups. Despite differences in data content, the logic of predictive classification is identical: learn patterns from past data to inform future service decisions.

2.3. Decision Support Systems

Decision support systems link analytical models to managerial action by integrating data, models, and human judgment (Power, 2002). In intelligent service systems, personalized classification models function as DSS components that recommend actions such as itinerary design or care pathway selection. Their purpose is not

simply to predict but to support decisions that improve service relevance, efficiency, and user satisfaction.

From a management science perspective, personalization is therefore a structured decision process embedded in service systems. It consists of segmentation, prediction, recommendation, adaptation, and feedback. These functions are common across tourism and healthcare, confirming that personalization is a transferable service methodology.

2.4. Personalization Functions Across Domains

Table 1 summarizes the core personalization functions in intelligent service systems and illustrates their parallel roles in tourism and healthcare. Each function operates at a different decision level and produces specific user impacts.

Table 1. Personalization Functions in Intelligent Service Systems

Function	Service Role	Tourism Example	Healthcare Example	Decision Level	User Impact
Segmentation	User grouping	Tourist personas	Patient cohorts	Strategic	Relevance
Prediction	Demand anticipation	Travel intent	Disease risk	Tactical	Accuracy
Recommendation	Service design	Itineraries	Care plans	Strategic	Satisfaction
Adaptation	Experience tuning	Dynamic pricing	Treatment intensity	Operational	Efficiency
Feedback	Learning loop	Reviews	Outcomes tracking	Governance	Trust

Table 1 shows that the same functional architecture underlies both domains. Segmentation structures the user population, prediction anticipates needs, recommendation designs services, adaptation tunes delivery, and feedback enables learning and trust. These shared mechanisms support the claim that tourist profiling and patient stratification are algorithmically and conceptually isomorphic.

3. Data Environments for Personalized Classification

Personalized classification depends on complex data environments composed of heterogeneous sources, formats, and temporal rhythms. In both tourism and healthcare, personalization is driven by the integration of behavioral, transactional, contextual, physiological, and feedback data. These environments illustrate that personalization is a data governance and management challenge rather than a purely technical modeling task.

3.1. Behavioral and Transactional Data

Behavioral data capture what users do over time. In tourism, this includes booking histories, website clicks, and GPS traces that reveal movement patterns and preferences (González, Hidalgo, & Barabási, 2008). In healthcare, behavioral analogues appear as treatment paths and care-seeking trajectories recorded in electronic health records (EHR). Transactional data such as payments or service utilization logs further document interactions between users and providers. These data enable intent modeling and service targeting.

3.2. Contextual and Physiological Data

Contextual data describe the conditions under which behavior occurs. In tourism, location, season, and event context shape travel decisions. In healthcare, age, comorbidities, and social context shape disease risk and care needs. Physiological data, such as biomarkers and laboratory results, add a biological dimension to personalization. Jensen et al. (2012) show that integrating molecular and clinical data improves stratification in complex health systems, demonstrating the role of high-dimensional data in classification-driven personalization.

3.3. Feedback and Outcome Data

Feedback data provide evaluative signals that support learning and adaptation. Tourism systems rely on reviews and ratings to refine recommendations and service design (Zhou, Ye, Pearce, & Wu, 2014). Healthcare systems increasingly use patient-reported outcomes and clinical results to evaluate and adapt care pathways (Murdoch & Detsky, 2013). These feedback loops transform personalization into an iterative governance process rather than a one-time prediction task.

3.4. User Data Structures Across Domains

Table 2 summarizes the main data layers used for personalized classification in tourism and healthcare and highlights their structural similarities.

Table 2. User Data Structures in Personalized Service Systems

Data Layer	Tourism	Healthcare	Structure	Frequency	Personalization Use
Behavioral	Clicks, bookings	Treatment paths	Semi-structured	Real-time	Intent modeling
Contextual	Location, season	Age, comorbidities	Structured	Periodic	Risk profiling
Feedback	Reviews	Patient-reported outcomes	Unstructured	Irregular	Experience tuning
Biological	–	Genomics, labs	High-dimensional	Periodic	Stratification
Policy	Tourism rules	Clinical guidelines	Structured	Periodic	Compliance

Table 2 demonstrates that differences between tourism and healthcare lie mainly in data content rather than data structure. Both domains manage multi-layered user data that require integration, classification, and governance. Personalized classification models operate on these layers to support segmentation, prediction, and service customization.

3.5. Implications for Personalized Service Systems

The convergence of data environments across domains reinforces the argument that personalization is a service system phenomenon. Whether using booking histories or biomarkers, intelligent service systems rely on classification to translate complex data into actionable service decisions. Tourism and healthcare thus represent two manifestations of the same methodological logic: data-driven personalization through classification and feedback.

4. Predictive Models for Personalized Services

Predictive models in intelligent service systems should be understood primarily through their decision outcomes rather than through their mathematical formulations. Their central role is to transform heterogeneous user data into actionable classifications that support personalized service design, delivery, and governance. Across tourism and healthcare, predictive models operationalize personalization through five interrelated functions: user profiling, behavior prediction, risk stratification, recommendation, and experience modeling. These functions demonstrate that tourist profiling and patient stratification share the same algorithmic logic within service systems.

4.1. User Profiling: Classification as Service Structuring

User profiling creates categorical representations of individuals that enable differentiated service strategies. In tourism, profiling generates tourist personas based on travel motivations, spending patterns, and mobility behaviors. In healthcare, profiling produces patient subtypes based on clinical characteristics, comorbidities, and care trajectories. The service outcome in both cases is relevance, as providers can tailor services to distinct groups rather than to undifferentiated populations.

From a service systems perspective, profiling reduces complexity by converting high-dimensional user data into manageable categories that guide planning and resource allocation (Wedel & Kannan, 2016). These profiles are not merely descriptive; they structure how organizations interact with users and how services are prioritized.

4.2. Behavior Prediction: Anticipating Needs and Intent

Behavior prediction models estimate future actions or needs based on historical data. In tourism, they forecast travel intent, destination choice, or spending behavior. In healthcare, they predict disease progression, hospitalization risk, or treatment response. The decision function is behavior forecasting, and the service outcome is accuracy in anticipating user needs.

Such models allow service systems to move from reactive to proactive management. Instead of responding after demand or risk materializes, organizations can intervene early with targeted services. This predictive logic underpins both recommendation systems in tourism platforms and early warning systems in healthcare governance (Murdoch & Detsky, 2013).

4.3. Risk Stratification: Prioritization under Constraints

Risk stratification classifies users according to vulnerability or urgency. Tourism systems use it to identify over-tourism zones or high-risk visitor segments, while healthcare systems use it to prioritize patients based on severity or likelihood of adverse outcomes. The decision function is risk grouping, and the service outcome is improved allocation efficiency and safety.

Obermeyer et al. (2019) show that algorithmic stratification strongly influences how resources are distributed and which users receive priority attention. This highlights that classification is inseparable from governance and service design. Whether allocating medical resources or managing visitor flows, stratification determines institutional action.

4.4. Recommendation Systems: Service Matching

Recommendation systems translate classification and prediction outputs into concrete service proposals. In tourism, this appears as itinerary design, attraction suggestions, or personalized pricing. In healthcare, it manifests as care pathway selection or treatment planning support. The decision function is service matching, and the service outcome is satisfaction, as users receive services aligned with their inferred needs.

Adomavicius and Tuzhilin (2005) argue that recommendation systems integrate user models with service options to maximize perceived value. In both tourism and healthcare, recommendations represent the operationalization of personalization, linking analytics directly to user experience and institutional performance.

4.5. Experience Modeling and Feedback Learning

Experience modeling and feedback learning close the personalization loop by incorporating user responses into future decisions. Tourism systems analyze reviews and ratings to refine service offerings. Healthcare systems use outcome data and patient-reported measures to adjust care pathways. The decision function is service refinement, and the service outcome is trust and continuous improvement.

This feedback-driven personalization transforms classification into a learning process rather than a static categorization. It also embeds personalization within governance structures by making service quality measurable and accountable (Power, 2002).

4.6. Comparative Roles of Predictive Models

Table 3 summarizes how predictive model types fulfill comparable decision roles in tourism and healthcare and generate similar service outcomes.

Table 3. Predictive Model Roles in Personalization

Model Type	Decision Function	Tourism Use	Healthcare Use	Service Outcome
Profiling	User classification	Tourist personas	Patient subtypes	Relevance
Prediction	Behavior forecasting	Travel intent	Risk progression	Accuracy
Recommendation	Service matching	Itinerary design	Care pathway	Satisfaction
Adaptation	Experience tuning	Pricing, offers	Treatment intensity	Efficiency
Feedback learning	Service refinement	Review mining	Outcome learning	Trust

Table 3 demonstrates that predictive models serve as decision mechanisms within service systems. Their purpose is not algorithmic elegance but the production of personalized, efficient, and trustworthy services. Tourism and healthcare differ in

content but converge in decision logic.

5. Real Case Data Sources

To ground personalized classification in real service systems, this study relies on publicly accessible and verifiable datasets from tourism and healthcare. These datasets represent large-scale environments in which predictive models support segmentation, prediction, and service customization.

5.1. Tourism Data Sources

The TripAdvisor Reviews Dataset provides millions of user-generated reviews and ratings of hotels, attractions, and restaurants. These data are widely used for preference modeling, sentiment analysis, and tourist profiling (Zhou et al., 2014). They enable the construction of personas based on expressed experiences and satisfaction levels.

Airbnb Open Data includes booking patterns, prices, and spatial distribution of accommodations across global cities. These data support demand prediction and segmentation of traveler types, offering insights into mobility and consumption behavior (Guttentag, 2015).

The UNWTO Smart Tourism Indicators dataset aggregates mobility statistics, policy indicators, and destination performance measures at national and regional levels. These data enable strategic personalization by aligning service design with broader tourism governance objectives (Citaristi, 2022).

5.2. Healthcare Data Sources

The MIMIC-IV Clinical Database contains de-identified electronic health records from over 300,000 patients in intensive care units. It is widely used for patient stratification and predictive modeling of risk and outcomes (Johnson et al., 2023).

The UK Biobank provides longitudinal health, lifestyle, and genetic data from approximately 500,000 participants. Its scale and diversity support robust risk modeling and personalized health stratification (Bycroft et al., 2018).

The NIH All of Us Research Program collects large-scale longitudinal health data from diverse populations in the United States, enabling personalization research and the study of heterogeneous care pathways (Ramirez et al., 2022).

5.3. Comparative Dataset Roles

These datasets differ in content but share structural features: high dimensionality, heterogeneity, and relevance for service personalization. They enable classification-driven decisions in both tourism and healthcare systems. Table 4 summarizes their characteristics and uses.

Table 4. Personalization-Oriented Datasets

Dataset	Domain	Data Type	Scale	Use
TripAdvisor	Tourism	Reviews, ratings	Millions	Preference modeling
Airbnb	Tourism	Booking, prices	Global	Demand prediction
UNWTO Indicators	Tourism	Mobility, policy	Global	Strategy design
MIMIC-IV	Healthcare	EHR	>300k patients	Stratification
UK Biobank	Healthcare	Health + genetics	500k	Risk modeling
All of Us	Healthcare	Longitudinal	Millions	Personalization

5.4. Implications for Personalized Classification

The use of these datasets confirms that personalization operates within large-scale service data infrastructures rather than isolated analytical tasks. Tourism and healthcare provide contrasting but methodologically equivalent contexts in which classification models transform complex data into service decisions. This reinforces the argument that tourist profiling and patient stratification are algorithmically common forms of personalized service classification.

6. Personalized Decision Outcomes

Personalized classification models reshape service systems by linking analytical outputs directly to decision outcomes. Their effectiveness is not determined solely by predictive accuracy, but by their capacity to improve user satisfaction, service relevance, resource efficiency, and experience quality. These dimensions capture the managerial and service value of personalization across tourism and healthcare systems.

6.1. User Satisfaction and Service Relevance

User satisfaction represents the extent to which personalized services align with individual expectations and needs. In tourism, satisfaction is reflected in experience ratings, repeat visitation, and positive reviews. Classification-driven personalization enables platforms to recommend attractions, accommodations, and itineraries that correspond to tourist personas and predicted preferences. In healthcare, satisfaction emerges through improved patient outcomes and perceived quality of care, supported by stratification models that match patients with appropriate care pathways.

De Keyser et al. (2019) argue that personalization enhances customer experience by increasing perceived relevance and reducing cognitive effort. This insight applies equally to healthcare, where stratification reduces uncertainty for both patients and administrators by clarifying service priorities. In both domains, classification functions as a relevance filter that translates complex data into meaningful service differentiation.

6.2. Resource Efficiency and Operational Performance

Personalized classification also contributes to resource efficiency. Tourism systems use segmentation and prediction to optimize service delivery, such as allocating staff to high-demand areas or adjusting pricing strategies dynamically. Healthcare systems use risk grouping and stratification to target limited resources toward high-need patients, improving cost control and system sustainability (Porter, 2010).

From a service systems perspective, efficiency is not merely technical optimization but institutional performance. It reflects how well organizations align service supply with heterogeneous user demand. Personalized classification reduces waste by preventing over-provisioning and under-utilization, transforming analytics into actionable operational strategies.

6.3. Responsiveness and Experience Quality

Responsiveness captures how quickly and flexibly service systems adapt to changing user needs. In tourism, dynamic offers and adaptive pricing respond to fluctuations in travel demand and user behavior. In healthcare, adaptive care pathways respond to evolving patient conditions and risk levels. These mechanisms enhance experience quality by ensuring that services remain timely and context-sensitive.

Kumar et al. (2021) emphasize that data-driven personalization enables firms to manage customer journeys dynamically rather than statically. Applied to healthcare, this logic supports continuous adjustment of care strategies based on patient feedback and outcomes. Experience quality thus becomes a function of classification accuracy combined with system adaptability.

6.4. Integrated Performance Dimensions

The combined effect of satisfaction, relevance, efficiency, and responsiveness defines the overall service impact of personalized classification. These outcomes move evaluation beyond algorithmic metrics toward service and governance performance. Table 5 summarizes the key personalization performance metrics across tourism and healthcare systems.

Table 5. Personalization Performance Metrics

Metric	Tourism	Healthcare	Service Impact
Accuracy	Preference match	Risk grouping	Relevance
Efficiency	Service delivery	Resource targeting	Cost control
Responsiveness	Dynamic offers	Adaptive care	Timeliness
Satisfaction	Experience ratings	Patient outcomes	Trust

Table 5 demonstrates that although tourism and healthcare differ in service content, the performance logic of personalization is structurally identical. Both domains rely on classification to enhance relevance, control costs, and build trust. Personalized decision outcomes therefore constitute a shared service system architecture rather than domain-specific achievements.

7. Governance, Ethics & Trust

The expansion of personalized classification models raises governance challenges that extend beyond technical design. The central concerns relate to algorithmic personalization governance, transparency of recommendations, user trust, data accountability, and institutional responsibility. These issues define the ethical and managerial foundations of intelligent service systems.

7.1. Algorithmic Personalization Governance

Algorithmic governance refers to the institutional frameworks that regulate how algorithms influence decisions and actions. In tourism, governance structures define how recommendation systems shape visitor flows and commercial strategies. In healthcare, they regulate how stratification models guide resource allocation and service prioritization. Floridi et al. (2018) argue that governance must ensure that AI systems align with societal values such as fairness, accountability, and transparency. Personalized classification therefore requires explicit rules regarding data use, decision authority, and oversight.

7.2. Transparency of Recommendations

Transparency is essential for legitimacy. Users and stakeholders must understand why particular recommendations or classifications are produced. In tourism, transparency affects whether travelers trust suggested itineraries or pricing strategies. In healthcare, it affects whether administrators and patients accept stratification-driven care pathways. Mittelstadt et al. (2016) emphasize that opaque algorithms undermine accountability and erode trust. Transparent personalization involves not only explainable models but also communicable rationales that link classification outcomes to service decisions.

7.3. User Trust and Data Accountability

Trust is built when personalization systems demonstrate reliability, fairness, and respect for user data. In tourism, trust is reflected in sustained platform engagement and positive perceptions of recommendation quality. In healthcare, trust is linked to confidence in institutional decision-making and protection of sensitive data. Pasquale (2015) highlights that accountability mechanisms are necessary to prevent automated systems from becoming unchallengeable authorities. Data accountability thus includes clear documentation of data sources, model assumptions, and decision consequences.

7.4. Institutional Responsibility

Institutional responsibility refers to the obligation of organizations to manage personalization systems ethically and strategically. This includes setting boundaries on automated decisions, maintaining human oversight, and ensuring that

classification outcomes support service goals rather than distort them. Governance structures must clarify who is responsible when personalized decisions produce adverse effects. In both tourism and healthcare, responsibility cannot be delegated entirely to algorithms; it remains an organizational and managerial duty.

7.5. Governance as a Service System Principle

Importantly, these governance issues are not domain-specific ethical dilemmas but service system governance challenges. The same principles apply to tourist profiling and patient stratification: transparency, accountability, and trust must be embedded into personalization architectures. This confirms that personalization is a managerial and institutional phenomenon rather than a clinical or technical one.

Together, governance and trust transform personalized classification from a predictive tool into a legitimate service mechanism. Without such structures, even accurate models risk rejection or misuse. With them, personalization becomes a sustainable foundation for intelligent service systems.

8. Cross-Domain Synthesis

The central finding of this study is that personalization constitutes a service system logic rather than a medical logic. Although tourist profiling and patient stratification appear to belong to fundamentally different sectors, they are governed by the same analytical and managerial principles: segmentation, prediction, recommendation, adaptation, and feedback. These functions define a transferable personalization architecture that operates across intelligent service systems.

From a service systems perspective, personalization is a mechanism for coping with heterogeneity and uncertainty in user populations. Ostrom et al. (2015) conceptualize service systems as configurations of people, technology, and organizations that co-create value through information exchange and coordinated action. Within this framework, classification models serve as decision infrastructures that translate complex data into actionable service categories. Whether the system is organizing tourists into experience segments or patients into risk cohorts, the managerial objective is the same: to enable differentiated service provision under resource constraints.

Predictive analytics further reinforces this logic. Shmueli (2010) distinguishes explanatory modeling from predictive modeling, emphasizing that prediction-oriented models are designed to support decisions rather than to test theory. Personalized classification models in both tourism and healthcare belong to this predictive tradition. Their value lies not in clinical discovery or behavioral explanation alone, but in guiding operational and strategic actions such as itinerary design or care pathway allocation.

Recommendation and adaptation represent the operational layer of personalization. Özen & Özgül (2023) show that recommender systems enhance user trust and

decision quality when they are perceived as useful and transparent. This applies equally to travel platforms and healthcare management systems. In both domains, classification outputs must be intelligible and actionable to be accepted by users and institutions. Feedback mechanisms close the loop by learning from outcomes and refining service strategies over time.

Table 6 synthesizes this cross-domain logic by mapping personalization functions across tourism, healthcare, and smart services more broadly.

Table 6. Transferability of Personalization Logic

Function	Tourism	Healthcare	Smart Services
Segmentation	✔	✔	✔
Prediction	✔	✔	✔
Recommendation	✔	✔	✔
Adaptation	✔	✔	✔
Feedback	✔	✔	✔

Table 6 demonstrates that the same personalization functions operate across domains with different data contents and risk levels. Tourism relies on behavioral and preference data, healthcare on clinical and physiological data, yet the underlying classification logic remains consistent. This confirms that personalization is not sector-bound but structurally transferable as a service system methodology.

The cross-domain synthesis therefore reframes patient stratification as a form of personalized service design rather than as a purely medical categorization task. Likewise, tourist profiling is elevated from a marketing technique to a generalizable model of intelligent service personalization. Both are instantiations of a broader management science paradigm in which classification enables strategic differentiation, operational efficiency, and governance accountability.

9. Conclusion

This study has demonstrated that personalized classification models represent a unifying methodological foundation for intelligent service systems. By comparing tourist profiling and patient stratification, the analysis shows that personalization is governed by shared decision functions-segmentation, prediction, recommendation, adaptation, and feedback-rather than by domain-specific knowledge structures.

The findings support a redefinition of personalization as a management science and service system methodology. Healthcare appears in this framework as an application case characterized by high stakes and complex data, not as the conceptual core of personalization research. Tourism, by contrast, provides the methodological origin of many personalization practices through recommendation systems, experience optimization, and customer segmentation. Together, they illustrate that personalized classification is fundamentally a service design and governance mechanism.

This perspective carries three main implications. First, it advances theory by integrating service-dominant logic and predictive analytics into a unified model of

personalized decision-making. Second, it informs practice by encouraging institutions to evaluate personalization in terms of service relevance, efficiency, transparency, and trust rather than technical accuracy alone. Third, it establishes transferability as a guiding principle: methods developed in tourism can inform healthcare personalization, and vice versa, through shared service system logic.

In terms of scholarly identity, this work positions the author as a researcher of personalized service systems, AI-enabled classification, and management science methodology. Healthcare is treated as a comparative application context, tourism as the methodological origin, and personalization models as service science tools. The contribution therefore lies not in advancing medical algorithms, but in articulating a cross-domain framework for understanding how classification enables personalization in intelligent service systems.

Ultimately, the study confirms that personalization is neither a medical innovation nor a tourism-specific technique. It is a generalizable service system logic that reshapes how organizations classify users, design services, and govern decision-making in the age of artificial intelligence.

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References

[1] Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE transactions on knowledge and data engineering, 17(6), 734-749.

[2] Bycroft, C., Freeman, C., Petkova, D., Band, G., Elliott, L. T., Sharp, K., ... & Marchini, J. (2018). The UK Biobank resource with deep phenotyping and genomic data. Nature, 562(7726), 203-209.

[3] Citaristi, I. (2022). World tourism organization-UNWTO. In The Europa Directory of International Organizations 2022 (pp. 404-407). Routledge.

[4] De Keyser, A., Köcher, S., Alkire, L., Verbeeck, C., & Kandampully, J. (2019). Frontline service technology infusion: conceptual archetypes and future research directions. Journal of Service Management, 30(1), 156-183.

[5] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Vayena, E. (2018). AI4People-An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and machines, 28(4), 689-707.

[6] Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. nature, 453(7196), 779-782.

[7] Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: foundations and developments. Electronic markets, 25(3), 179-188.

[8] Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. Current issues in Tourism, 18(12), 1192-1217.

[9] Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning.

[10] Jensen, P. B., Jensen, L. J., & Brunak, S. (2012). Mining electronic health records: towards better research applications and clinical care. Nature Reviews Genetics, 13(6), 395-405.

[11] Johnson, A. E., Bulgarelli, L., Shen, L., Gayles, A., Shammout, A., Horng, S., ... & Mark, R. G. (2023). MIMIC-IV, a freely accessible electronic health record dataset. Scientific data, 10(1), 1.

[12] Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. Journal of Business Research, 125, 864-877.

[13] Lusch, R. F., & Nambisan, S. (2015). Service innovation. MIS quarterly, 39(1), 155-176.

[14] Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2), 2053951716679679.

[15] Murdoch, T. B., & Detsky, A. S. (2013). The inevitable application of big data to health care. Jama, 309(13), 1351-1352.

[16] Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447-453.

[17] Ostrom, A. L., Parasuraman, A., Bowen, D. E., Patrício, L., & Voss, C. A. (2015). Service research priorities in a rapidly changing context. Journal of service research, 18(2), 127-159.

[18] Özen, İ. A., & Özgül Katlav, E. (2023). Aspect-based sentiment analysis on online customer reviews: a case study of technology-supported hotels. Journal of Hospitality and Tourism Technology, 14(2), 102-120.

[19] Parasuraman, A. B. L. L., Zeithaml, V. A., & Berry, L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. 1988, 64(1), 12-40.

[20] Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. In The black box society. Harvard university press.

[21] Pine, J. B., & Gilmore, J. H. (1999). The Experience Economy Boston.

[22] Porter, M. E. (2010). What is value in health care?. New England Journal of Medicine, 363(26), 2477-2481.

[23] Power, D. J. (2002). Decision support systems: concepts and resources for managers. Studies in Informatics and Control, 11(4), 349-350.

[24] Ramirez, A. H., Sulieman, L., Schlueter, D. J., Halvorson, A., Qian, J., Ratsimbazafy, F., ... & Wellis, D. (2022). The All of Us Research Program: data quality, utility, and diversity. Patterns, 3(8).

[25] Shmueli, G. (2010). To explain or to predict?. Statistical science, 289-310.

[26] Vargo, S. L., & Lusch, R. F. (2014). Evolving to a new dominant logic for marketing. In The service-dominant logic of marketing (pp. 3-28). Routledge.

[27] Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of marketing, 80(6), 97-121.