Computer Fraud and Security
ISSN (online): 1873-7056

AI-Powered UI Personalization for Customer Self-Service in Hybrid Cloud Environments

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Abstract

User interface personalization and user experience enrichment have been explored separately in different contexts and domains, but in customer self-service interactions deployment in hybrid cloud environments there is no evidence of such merging for enhancing customer experience. Therefore, the main contribution of this article is the evidence-based design and development of an AI-powered user-interface-personalization component predominantly for customer self-service interactions in hybrid cloud environments. A process-oriented ontology of user-interface personalization is defined and the specific formulation of a user-interface-personalization function expresses how and why AI services and systems relevant for customer self-service interactions are personalized.

Actionable items for business process management and development, customer experience management, and marketing communication are derived from the interplay of personalization functions as a two-way customer-interface-network relationship that support user-interface personalization towards specific business objectivesevolving across three stageshealth optimisation, process enabler, and process enhancer. These stages define four user-interface-personalization taxonomies with customer self-service context—chatbots, virtual assistants, machine-learning customer serviceanswers components—and the related four generated business-objective classifications concentration, engagement, knowledge-generation, and innovation-enhancement enrichmentextendable to hybrid-cloud-contextualised user experience design and interaction design for any specific user-interface personalization function.

Keywords :AI-powered UI personalization,Customer self-service automation,Hybrid cloud user experience,Adaptive interface design,Intelligent customer portals,Context-aware personalization,Cloud-native self-service platforms,Machine learning UX optimization,Personalized digital support systems,Enterprise hybrid cloud UX AI.

1. Introduction

Hybrid cloud environments are rapidly gaining traction for their ability to deploy and run customer-facing services in a cost-effective manner. Such services are typically web applications that provide self-service capabilities for customers without the need for additional infrastructure, server, and application overhead when there are no requests. For such systems, the reduced utilization often leads to poor user experience: users receive responses from the application with delays. Furthermore, as the number of customers grows, a customer's requests become more frequent, often consisting of similar queries; consequently, the answers provided by the application are also often similar and can thus be offered in a more efficient manner. AI-powered personalization automates this process by predicting which responses are needed before the actual requests come in.

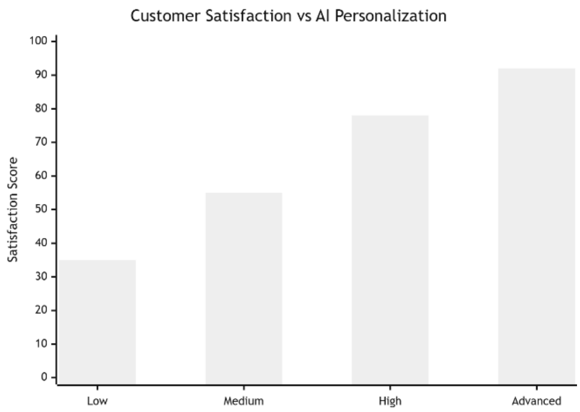
Innovative technologies, data-oriented business models, and customer experience are key factors in the global competition among service providers. Use of AI relies on many sources of information, including CRM and SCMS databases, browsing history, and more. However, these databases do not contain the required information on previous user experience with the UI. Data for training AI personalization systems is generally extracted from various sources and combined for use in data-driven machine-learning algorithms; the stitching together of data from different, disparate sources is called data integration. However, the models must also have sufficient accuracy; if they do not, users will not engage with the service. Therefore, data quality is critical and has a recursive effect on data integration. Personalization systems that do have these records provide a much richer and data-driven approach, enabling continual automated adaptation.

Component	Function	Technologies Used	Business Benefit
User Profile Engine	Maintains customer behavior and preferences	ML, NLP, Knowledge Graphs	Personalized experience
Recommendation Engine	Predicts suitable services and responses	AI Models, Predictive Analytics	Faster issue resolution
Data Integration Layer	Combines multi-source cloud data	ETL, APIs, Data Lakes	Unified customer insights
Taxonomy Manager	Organizes service categories dynamically	Ontologies, Semantic AI	Intelligent navigation
Sentiment Analyzer	Detects emotional tone of users	NLP, Deep Learning	Improved engagement
Hybrid Cloud Orchestrator	Balances workloads across clouds	Kubernetes, Cloud APIs	Scalability and efficiency

Table 1. Core Components of AI-Powered UI Personalization

1.1. Research design

This work demonstrates a multi-method, development-oriented research approach that designs, builds, and prototypes a complex environment. The prototype enables AI-driven user interface personalization to facilitate new customer self-service capabilities in hybrid cloud environments that integrate services and deployments from multiple public and private providers.



Customer Satisfaction vs Personalization Level

2. Background and Fundamentals

A hybrid cloud architecture connects any combination of memory, processing, and storage in local data centers with cloud resources in a manner sufficient to achieve transparency, elasticity, load balancing, workload rebalancing, etc., while maintaining privacy of sensitive customer data.

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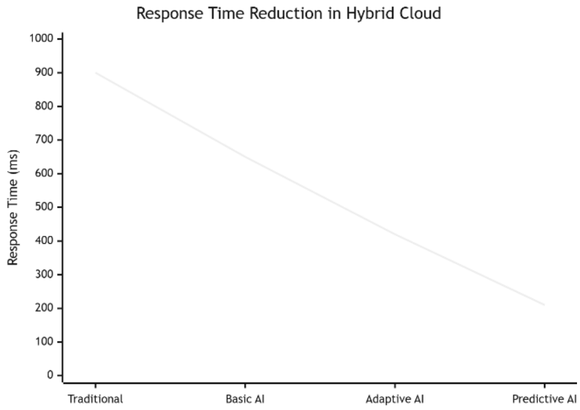
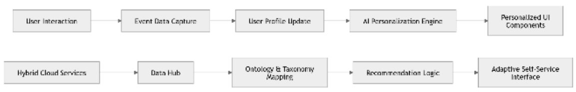
A hybrid cloud deployment model combines one or more hybrid cloud components in a manner sufficient to achieve transparency, elasticity, load balancing, workload rebalancing, etc., while maintaining privacy of sensitive customer data. Examples include services that use a private cloud to process private data and distribute results via the public cloud (protected by a Service Level Agreement (SLA)), and services that delegate performance-sensitive data processing to a local data center with overflow executed in the public cloud. Hybrid federations enable exchange of data while preserving privacy and/or meeting performance constraints. Secure and Elastic Public-Private Cloud Broadcasting (SEPBCB) enables Private-Key-Preferred, security-enforcing public-private key cloud broadcasting for hybrid cloud deployment in e-businesses. Hybrid cloud burst capabilities enable efficient resource management across private and public cloud sources.



Hybrid Cloud Response Time Optimization



AI-Powered UI Personalization Flow

2.1. Hybrid Cloud Architectures

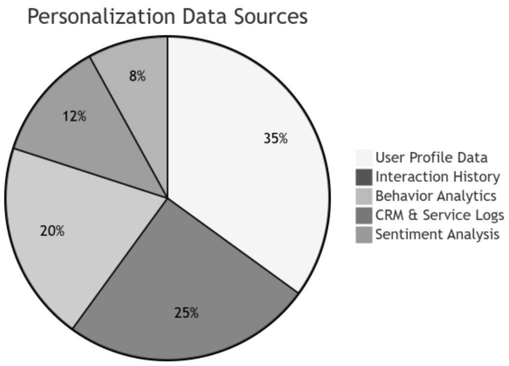
Although the combination of public and private cloud services in a hybrid architecture paradigm offers considerable flexibility, cloud providers still struggle to deliver services that fully exploit this potential. Providers can use hybrid clouds to guarantee key performance indicators, optimize the use of network resources or avoid sending sensitive data onto an untrusted infrastructure. However, when a set of user requests requires services in the public cloud, personalization of the user interface, which is usually based on the services perceived as closer, is lost. AI-powered user interface personalization enables customers not only to find information more easily but also to better interact with the system through the provision of specific services and information according to their needs. This enhanced capability for personalization in hybrid cloud environments exploits the contextual, temporal and logical relationship of the data available.

Data Source	Data Type	Purpose in Personalization	Example
CRM Systems	Structured	Customer history analysis	Purchase records
Browsing Logs	Semi-structured	Behavioral prediction	Search activity
Chatbot Conversations	Unstructured	Intent recognition	Customer queries
Social Media Feeds	Unstructured	Sentiment extraction	Comments and reactions
IoT/Device Events	Streaming	Context-aware adaptation	Device usage patterns
Support Tickets	Structured	Recommendation learning	Incident history

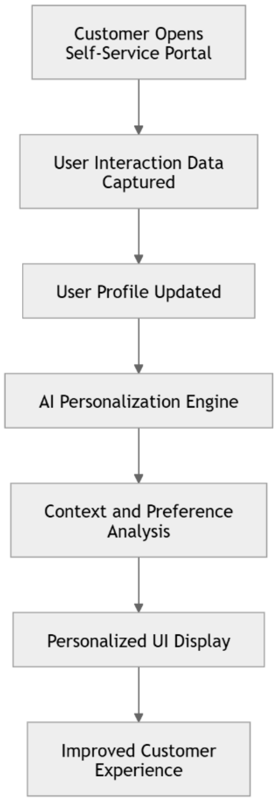
Table 2. Hybrid Cloud Personalization Data Sources

3. Data, Governance, and Ethics

Data sources have a strong influence on the adaptation of a dynamic UI and play an important role in the quality of a personalized service for a customer. The customer data that is required and helpful for the personalization process are stored in a central repository called the data hub. This hub is essential because it is a common repository for language models, text analysis models, approaches to natural language processing (NLP), text and video information about services, image libraries, and so on. The personality of the user is stored in a centralized persona management module. This module includes demographic data from the customer site. The gathered information is not only used for initial analysis but is also updated permanently to reflect the knowledge about the customer. For example, maintaining the history of purchased services is a crucial requirement when GDPR compliance is an issue. Data about how a person interacts with the self-service application can be collected and analyzed to continuously improve the service that is delivered and the dialogue that is offered.



Data Source Contribution to Personalization



AI-Powered UI Personalization Process

3.1. Data Sources for Personalization

Structuring an AI-Powered User Interface Personalization Mechanism requires various data sources. The most significant source of personalization data is the User Profile, which is stored and maintained in a dedicated Knowledge Base information system. Sections 3.1.1 to 3.1.6 summarise the structure and data stored in the User Profile, and highlight the impact of the User Profile in the decision-making processes of the AI personalization mechanism. Other data sources required by the User Profile, and populated by the User, are also discussed. The Event Data source stores real-time event data generated during user interaction with the Information and Communication Technology self-service interface.

The User Profile (UP) is structured as a hybrid cloud Knowledge Base information system. It contains information related to the Human Actor and the User's interaction with the ICT Help-Desk and Telecommunications Network services. It undergoes an update after each event generated by the A-user interaction with the system, with the exception of the characteristics that can only be modified by the User. The information structure includes the User's most representative social network (e.g. Facebook, Instagram, LinkedIn, and others); the demographic characteristics of the User; list of messages labelled by the system; User sentiment profile; last interaction with the self-service platform; preferred language; preferences of interaction of the U-user; spelling and grammatical errors associated with the User; attention level (e.g. Under- attention, Over-attention, Normal attention); level of emotional involvement (e.g. High, Medium, Low); level of cognitive involvement (e.g. High, Medium, Low); level of action involvement (e.g. High, Medium, Low); Interest groups; and Thematic index of images and videos posted.

Hybrid Cloud Customer Self-Service Flow

Taxonomy Category	Description	Personalization Outcome
Chatbots	Automated conversational support	Faster customer interaction
Virtual Assistants	Context-aware assistance	Intelligent guidance
ML-Based Recommendation Systems	Predictive suggestions	Increased engagement
Adaptive UI Components	Dynamic interface rendering	Improved usability
Knowledge-Based Systems	FAQ and ontology-driven support	Accurate information retrieval

Table 3. Personalization Taxonomy Categories

4. Methodologies and Technologies

A major challenge when implementing UI personalization in hybrid cloud IaaS and PaaS environments is integrating data from various systems into a common structure that is suitable for the personalization algorithms. An additional hurdle is guaranteeing data quality, given that poor data provenance can severely compromise the performance of any data-driven process, whether predictive or prescriptive. Structured data sources typically offer a higher level of data quality compared with unstructured ones. Nevertheless, unstructured data are increasingly playing an important role in feeding personalization algorithms (e.g., a user's previous search queries in Google). Some methods can help evaluate and improve the quality of data stored in a data lake. These methods can detect and remove duplicate data and spam. Moreover, parameterized analyses can identify and exclude users performing irrelevant searches that may not envisage suitable actions displayed in the mobile app.

Mathematical Formulas:

1. User Personalization Function

The personalization score for a user interface can be modeled as:

$$P_u = \sum_{i=1}^{n} w_i x_i$$

Where:

- P_u= personalization score for user u
- w_i= weight of contextual feature
- x_i= user interaction parameter

2. Recommendation Accuracy Model

Used for AI-based service recommendation efficiency.

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP= true positives
- TN= true negatives
- FP= false positives
- FN= false negatives

3. User Engagement Index

Measures customer interaction quality.

$$E = \frac{C + T + I}{3}$$

Where:

- C= click activity
- T= session time
- I= interaction frequency

4. Hybrid Cloud Response Time

Represents total response latency in hybrid environments.

$$R_t = L_n + P_t + D_t$$

Where:

- L_n= network latency
- P_t= processing time
- D_t= data transfer delay

5. AI Prediction Probability

Used in machine-learning personalization.

$$P(y \mid x) = \frac{e^{w \cdot x}}{1 + e^{w \cdot x}}$$

Where:

- x= feature vector
- w= learned model weights

6. Sentiment Analysis Score

Represents customer sentiment derived from interactions.

$$S = \frac{N_{pos} - N_{neg}}{N_{total}}$$

Where:

- N_{pos}= positive responses
- N_{neg}= negative responses
- N_{total}= total responses

7. Cloud Resource Utilization

Evaluates resource efficiency in hybrid cloud deployment.

$$U = \frac{R_{used}}{R_{total}} \times 100$$

Where:

- R_{used}= utilized resources
- R_{total}= available resources

8. Context-Aware Recommendation Score

Represents adaptive service recommendation.

$$CR = \alpha P + \beta C + \gamma H$$

Where:

- P= personalization factor
- C= contextual relevance
- H= historical behavior
- α, β, γ= weighting coefficients

9. Data Quality Metric

Used for evaluating integrated personalization datasets.

$$DQ = \frac{A_c + C_m + C_s}{3}$$

Where:

- A_c= accuracy
- C_m= completeness
- C_s= consistency

10. Dynamic UI Adaptation Function

Represents adaptive interface updates over time.

$$UI_t = UI_{t-1} + \Delta U$$

Where:

- UI_t= updated interface state

- ΔU= adaptive modification value

4.1. Data Integration and Quality

Hybrid cloud architectures combine multiple complementary systems, optimizing the balance of flexibility, performance, security, and cost. A customer self-service system supports personalized automatic services for external and internal customers. Data sources identified for customer ontology personalization include full-text descriptive online documentation, customer support repositories, service requests, and business process databases.

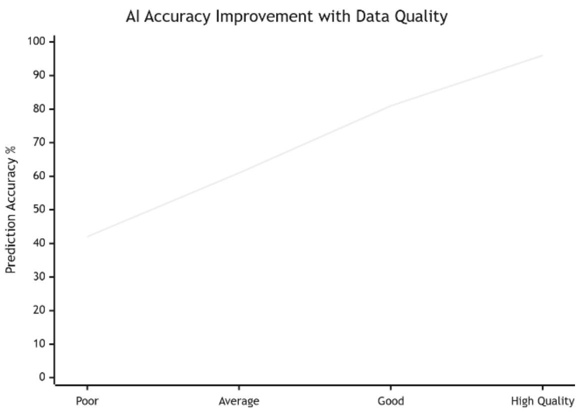
AI Technique	Role in System	Expected Output
Machine Learning	Pattern recognition	Service recommendations
Deep Learning	Complex behavior analysis	Personalized workflows
Natural Language Processing	Query understanding	Conversational responses
Sentiment Analysis	Emotion detection	Adaptive interaction
Recommendation Algorithms	Predictive assistance	Personalized suggestions
Reinforcement Learning	Interaction optimization	Continuous improvement

Table 4. AI Techniques Used in Customer Self-Service

5. System Architecture and Deployment

Personalization is sometimes regarded as a separate layer of an IT architecture, capable of stretching across clouds and/or different technologies. However, the integration of the system components, particularly those that support the horizontal services of personalization and recommendation, with the core customer service consequently resides in the customer service layer, the APIs, and sometimes even the actual presentation authority distribution and construction strategies.

Two key deployment models are established within the architecture: the hybrid cloud model holds the core customer service system, while the personalization and supporting services run in a public cloud. The usability of different data governance approaches that are defined at the ontology level is supported and extended with specific business rules. The resultant applications cover both standard request-response transactions of a customer service and different states of service interaction with (potential) customers where personal experience and service recommendation play an important part.



AI Model Accuracy vs Data Quality

5.1. Hybrid Cloud Deployment Models

The heterogeneous, multi-layered interconnected architecture of hybrid clouds allows the distribution of services to multiple customer enterprises and institutions, exploiting the diversity of cloud systems provided by public cloud providers and communities, as well as locally through private cloud infrastructures. Configuration and workload management are essential functions of hybrid-cloud computing since services and interconnections can vary over time, requiring continuous changes for optimization. Currently, the most used hybrid-cloud deployment model is the integration of private and public infrastructures.

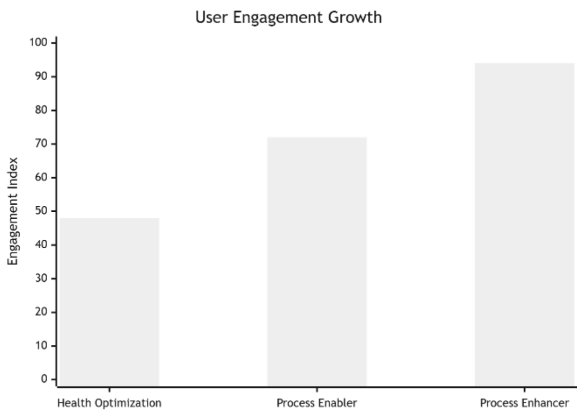
Governance Area	Objective	Technologies/Policies
GDPR Compliance	Protect user privacy	Consent management
Data Encryption	Secure cloud communication	AES, TLS
Access Control	Restrict unauthorized access	IAM, RBAC
Data Auditing	Track personalization activities	Logging frameworks
Data Minimization	Reduce unnecessary storage	Governance rules
Consent Lifecycle Management	Handle user permissions	Consent APIs

Table 5. Data Governance and Security Framework

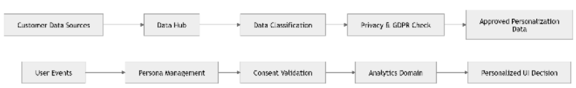
6. User Experience and Interaction Design

Personalization is realized through the configuration of taxonomies and ontologies that underpin user profile updates for the AI-powered User Interface. The taxonomies serve as a repository of expected user needs that can be satisfied automatically as the user interacts with the self-service tools and knowledge bases. The personalization modules for the AI-Powered User Interface dynamically derive relevant items from the external sources as required, updating them into the taxonomy registers. The current AI-Powered User Interface trial is implicitly observing user events—such as tagging items as useful or not useful—to produce a personalized hierarchy of services, tools, or knowledges, which are then made available through the service request box within the user-specific box. For customers with a single service management tool, the hierarchy is shown as a pull-down menu.

To expand personalization, the elements of a second-level taxonomy—the expectations of customers, groups, or roles—are used. Due to the nature of support and self-service in the telecommunications sector, the user interactions as service support fulfil the expected customer groups of an external audience. Thus, a taxonomy of profile updates enables expected incidents for different levels of support to be made accessible to the AI-Powered User Interface through a client profile feed. These expected incidents are then written into a second-level taxonomy and offered as a tagged property of the customer support agent. As customers interact with the AI-Powered User Interface and mark these incidents as useful or not useful, the system continuously updates its taxonomy and provides a ready solution or guidance for developers as a customer intern administration service in service management tools.



User Engagement Across Personalization Stages

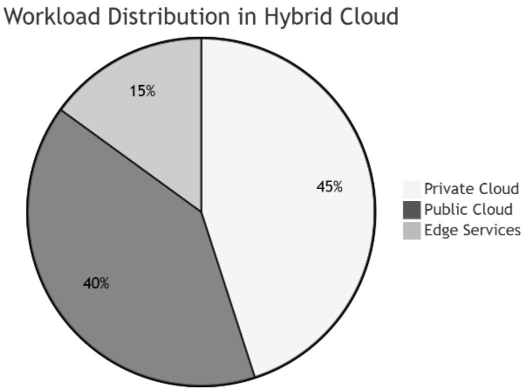


Data Governance and Personalization Flow

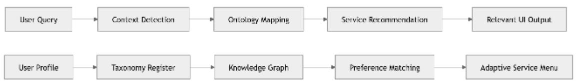
7. Conclusion

In commercial organizations as well as larger public institutions, self-service and support services are delivered through customer relationship management systems that are more or less tailored toward the customers. In hybrid cloud environments, these systems can easily be deployed close to customers and users in edge regions. A growing investment in edge cloud computing along with AI infrastructure as a service services opens the opportunity for both private and public organizations to utilize advanced artificial intelligence capabilities in hybrid cloud environments.

While most of these cloud resources offer instrumentation functionalities that can be beneficial for companies in respect of an improved data-sequencing and event-trackin architecture, these functionalities can also be exploited by data-creator companies that offer support services for consumer-product providers. Functionality created through marketplace a6pplications enables those organizations to create perspective-enriched interaction services. In combination with instrumentation supports, monetized AI components can enforce the direct support interfaces between consumers and wider product-support organizations. These opportunities change the self-service segments as well as the two-sided revenue systems of consumer-product-support interfaces into virtual marketplaces for direct user interactions.



Hybrid Cloud Workload Distribution



Ontology-Based Personalization Flow

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