Context-Aware Virtual Assistants for Enterprise Service Platforms

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Abstract

The emerging trends of Enterprise Service Platforms (ESPs) and Enterprise Service Marketplaces (ESMs) promise a tremendous change in the way enterprises consume and deliver services. The increasing number of service offerings along with the ever-growing catalog complexities are moving users and providers further apart in the traditional service business models. Leading technology companies are beginning to shift their focus toward service transaction automation and delegation. Virtual Assistants (VAs) have gained much interest across multiple contexts. However, the current state of the art is still fragmented and limited in terms of providing an overall, integrated, and structured reflection of the application of VAs in the domain of ESPs or ESMs. This scholarly work discusses the emerging demand for context-aware VAs to support, accelerate, and automate service transactions in ESPs and ESMs.

Context-aware VAs should be explored based on the concept of context awareness, whose theoretical foundations and architectural patterns are examined first. The definition and functionalities of context-aware VAs are then analyzed, followed by a discussion of their integration into ESPs and ESMs. Finally, the detection and prevention of privacy-related issues, as well as Privacy-By-Design and Privacy-By-Default perspectives, are addressed. An overview of existing research and future research directions conclude the study.

Keywords: Enterprise Service Platforms (ESPs), Enterprise Service Marketplaces (ESMs), Service Transaction Automation, Context-Aware Virtual Assistants, Intelligent Service Delegation, Service Catalog Complexity Management, Context Awareness Models, Context Modeling and Reasoning, Virtual Assistant Architectures, AI-Driven Service Consumption, Automated Service Brokerage, Human–Service Interaction, Intelligent Service Discovery, Personalized Service Delivery, Enterprise Automation Ecosystems, Privacy-Aware Virtual Assistants, Privacy-By-Design, Privacy-By-Default, Secure Service Interaction, Future Enterprise Service Models.

1. Introduction

Virtual assistants have gained considerable popularity among users. Their widespread availability on smartphones and other personal devices supports mundane activities such as searching for information, making reservations, or ordering meals. Context-aware techniques enable an automatic adaptation of the virtual assistant's behavior to the user, increasing the overall experience. A similar approach within enterprise environments would enhance the overall experience and productivity of employees working with enterprise service platforms (ESP). Within an ESP context, a VA could help users by answering questions, automatically generating knowledge articles, and providing decision support. The need for a context-aware solution becomes even more pressing when considering the increasing number of VAs with generative artificial intelligence capabilities. The combined forces of these technologies allow a VA to answer complicated and complex questions appropriately. Integrating a VA and context-aware techniques with an ESP opens the door to additional possible capabilities such as automating mundane tasks, enhancing document retrieval, providing recommendation support, and ensuring policy compliance. Implementing a context-aware VA requires groundwork in context-aware technologies and a clear architecture that positions the VA within an ESP. Several aspects must also be covered, including possible commercial context-aware VAs, the levels of context awareness supported, data governance, integrated tools, and the evaluation of a context-aware VA. Subsequently, several representative use cases demonstrate how the use of a context-aware VA provides additional business value. The overview covers the foundations of context-aware technologies and discusses how context-awareness can benefit the employee experience and productivity in ESP-enabled organizations.

Context-aware systems have seen significant growth within the last decade. Initially, the focus was to enhance mobile products with context awareness, such as context-aware smartphones, tablets, displays, or cameras. Yet contexts can also help within static environments such as corporate information systems where employees interact with multiple tools and documents; organizational external context would allow such systems to adapt behavior and functions to the actual user and data situation. Applying context-aware techniques within Enterprise Service Platforms can help emulate a human-like interface with employees, driving innovation and user experience.

1.1. Overview of Context-Aware Technologies

Context-Aware Virtual Assistants for Enterprise Service Platforms should be studied with an objective, evidence-based approach, emphasizing formal structure and clear presentation. The advent of context-aware technologies has moved the area of artificial intelligence beyond logical and statistical frameworks to encompass semantics rooted in perceptual and situational relations. Clearly defined context models and rich representations of context not only support knowledge-enabled and knowledge-based systems, but also provide the foundation for the next generation of virtual assistants (VAs).

Context-aware VAs are well placed to retrieve domain knowledge in terms of concrete instances, interrelate knowledge from various sources (knowledge bases, knowledge graphs, knowledge bases, and emergent knowledge enabled by LLMs), synthesize results in a conversational manner, automate discrete tasks, and support decision making during ill-defined tasks. A rich history of context-aware operations has been reported in the literature, with examples including context-enabled adaptive Systems, context-aware Web services and middleware, and context-aware mobile applications.

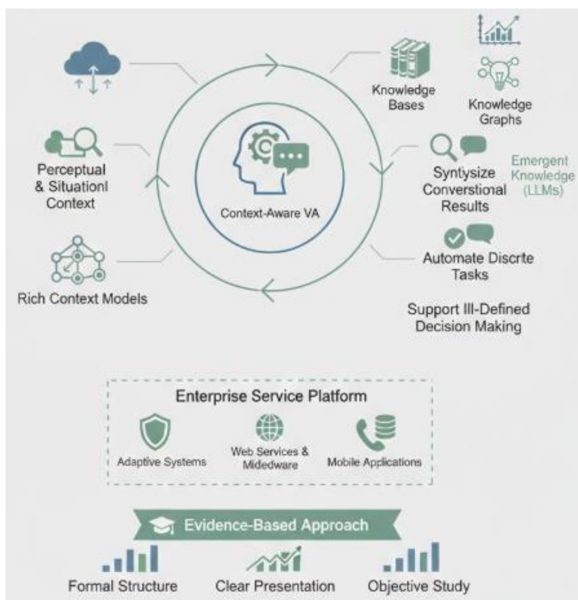

Fig 1: Beyond Logic and Statistics: A Formal Framework for Context-Aware Virtual Assistants in Enterprise Service Platforms

2. Foundations of Context Awareness

Two major issues define the foundation of context awareness: theory and structure. Context awareness relies on a theory of context and on a context representation model. The theory informs the context model; the model is then used by the context-aware application throughout its life cycle in a generic way. Together, theory and structure provide a foundation that is flexible enough to encompass both sophisticated services in controlled environments (e.g., military, fire, and plumbing) and relatively simple context-aware applications in user environments (e.g., sensing the car driver, a user's busy schedule, and the desire for privacy).

Several properties of context are generally accepted: (a) context changes constantly, and changes must be carefully monitored and actively used by the applications; (b) the context changes can be sudden (e.g., an automobile crashes) or gradual (e.g., weather conditions) or both (e.g., an enterprise's stock market position); (c) context changes may not be observable but their presence may be inferred by a combination of observable changes; (d) larger changes in context can be composed of smaller changes; (e) some context variables just are not observable directly, but may be inferred by other indirect observations over time in a context that keeps repeating itself; and (f) context information never is complete, but always can be made consistent for some purpose.

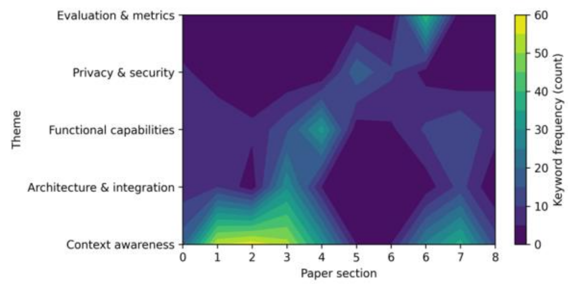

Fig 2: Contour-based visualization of thematic emphasis density across sections

Equation A. Context as a time-varying state

Step 1 — define a context state vector
Let the assistant's context at time t be a structured state:

$$\mathbf{c}(t) = \begin{bmatrix} c_1(t) \\ c_2(t) \\ \vdots \\ c_d(t) \end{bmatrix}$$

Each component could represent user role, device, location, active task, service catalog slice, policy constraints, etc.

Step 2 — observation model (some context isn't directly observable)
Let sensors/logs/platform signals be:

$$\mathbf{o}(t) = h\big(\mathbf{c}(t)\big) + \boldsymbol{\epsilon}(t)$$

where $h(\cdot)$ maps true context to what is observable, and ϵ is noise/missingness. This corresponds to the point that some context is inferred from other observable changes.

Step 3 — inference (estimating context from observations)
A generic estimator:

$$\hat{\mathbf{c}}(t) = \underset{\mathbf{c}}{\operatorname{argmax}}\ P(\mathbf{c} \mid \mathbf{o}(t), \mathbf{o}(t-1), \dots)$$

2.1. Theoretical underpinnings

The foundations of context awareness for virtual assistants (VAs) are based on the systematic investigation of context-aware systems, enriched with concepts from the domain of knowledge technology. Existing research work shows that innovations in the context-aware domain are also applicable to the development of VA-based systems. Knowledge technology empowers the construction and operation of intelligent systems, where knowledge is explicitly represented, processed, and utilized. Theoretical ideas of symbolic AI, language technology, and, in a broader extension, CNLs (Controlled Natural Languages) offer high-level models for the retrieval and synthesis of information.

Context-awareness, the technology for gathering and processing external information to enhance the system's performance, introduces another intelligent feature in the newly conceived VA-based assistants. The underlying architecture is layered without contradicting the original model. Context-aware methods have become an essential part of technology stacks to support the development of context-aware virtual assistants. Knowledge-based contexts are formal representations of knowledge technology in the context-aware domain and can be used to enhance the performance of context-aware VAs significantly.

Table 1. Core Elements and Quantitative Enumerations Used in the Study

Element (from paper enumerations)	Count
Properties of context (a–f)	6
Context representation categories	5
Layered architecture layers	4
Access-control guidelines	6
SUS questionnaire items	10

2.2. Context models and representations

Various context models and representations have been proposed to tackle a range of research problems across different domains. Existing context-based knowledge representation systems can be classified into five broad categories:

1. General Knowledge Representation Frameworks: These frameworks provide basic definitions of what constitutes context and context-awareness without reference to any particular domain. They concentrate on the formal representation of context and related reasoning processes. Examples are provided by the models of Dey and Abowd, Schilit et al., and Huang et al. These models support the definition of context but stop short of providing any specific representation or reasoning mechanisms.

2. Domain-Specific Context Representations: These representations focus on particular applications and define the domain-dependent context in detail. Within a car assistance application, for instance, a representation would include the driver information (e.g. identity, age, gender, recent events), the car status (locational trajectory) and performance, and the possibility of incoming events (e.g. morphology and context of an upcoming traffic light or police officer). Context is specified for a parking or road assistant car, explicitly modeling expected events (what's in the way, or where it may park). In smart retail, context comprises store layout, promotions, inventory, clients/testers' expectances, and history. Acquaintance knowledge can suppress or serve ads closer to a target location. Other domains, such as intelligent transportation systems, health, education, and marketing, also have their own definitions.

3. Context-Based Knowledge Networking Systems: Context networks use the notion of context to create users' and service knowledge based on correlations in their interactions. Context expresses what one perceived or delivered or what services were referenced or delved into. The context pattern of a specific user-service relationship helps in anticipating expected behavior in future interactions.

4. Context-Specific Knowledge Reasoning Systems: These systems model context for specific tasks, but the models do not permit context-specific support for reasoning. Context is for dialog management and user personalization.

5. Context Representation Subsystems in General Systems: Context is represented as a subsystem in a higher-level knowledge system.

3. Architecture of Context-Aware VAs

Layered architectural patterns for context awareness in VAs employ a core context-aware SOA with three functional layers. The context detection and context reasoner modules possess great genericity and can be reused in other enterprise context-aware applications. Novel components, such as the entity disambiguator and the data synthesis engine, as well as additional pieces of context information, address the particularities of enterprise assistants for the novel task of knowledge product synthesis. Implementation of such a layered architecture is supported by integration with enterprise service platforms, i.e., frameworks for integrating enterprise software applications and business data. Such platforms typically provide internal services of different specialties, including messaging, authentication, and pre-built connectors to enterprise systems for exchanging messages or performing operations.

Integration with a context-aware enterprise platform enhances the capabilities of enterprise-aware virtual assistants to cover more complex use cases. Moreover, such integration improves the management of context information and context-related operations, which can now take advantage of a set of reusable services. The combination of such services further extends the range of specialized context-enabled operations. Key extensions include the empowerment of enterprise assistants to search conversations from enterprise communication systems (e.g., Teams, Slack), provide summaries of such conversations and connect to external knowledge bases in order to enhance decision-making and problem-solving business processes.

3.1. Layered architectural patterns

Virtually all applications of the context-aware concept follow a layered architectural pattern including:

• A context-aware data storage layer, responsible for the definition of sophisticated logical structures for the storage of context data, for instantiating such structures, and for du-plicating context information from one context source to another, based on specific demands.

• A context-awareness decision layer, where context information from different sources is collected and semantically fused.

• A context-service layer, aimed at supporting user and application detection of relevant context information and its subscription.

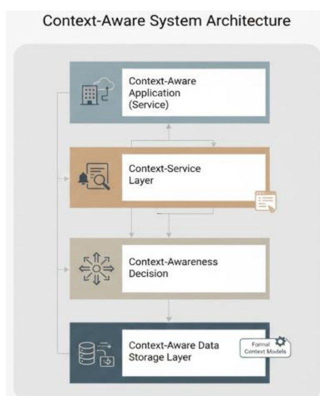

Fig 3: Decoupling Context: A Layered Formal Architecture for Semantic Context-Aware Management Systems

• A context-aware application (service) layer, offering the support for business applications to detect relevant context data sources and to retrieve the information, if needed.

To operate through such layers, formal context models are usually defined, enabling an unambiguous formal representation of context information, independent of its physical instantiation. Dedicated context-aware management systems may be built for managing context representation and access. Context models contents are accessed according to their semantics through dedicated, context-service-oriented interfaces.

3.2. Integration with enterprise service platforms

Enterprise service platforms provide the foundation for integrating service- and customer-facing functions within an organization. These platforms encompass software systems that organize and manage enterprise resources; underlying business processes; supply chain management flows; service requests; or production, logistics, and delivery operations. They can serve as primary repositories for structured data relevant to completing operational tasks, and they can also make available supporting information that helps service professionals assist customers. Virtual assistants may operate independently but are expected to be integrated with enterprise service platforms in a way that allows them to facilitate tasks undertaken by service- or customer-facing employees.

Integrating context-aware VAs with enterprise service platforms requires defining the information to be extracted from the platforms, identifying the context in which the VAs will provide contextual help, and detailing how the VAs will cleanse and structure the extracted data into contextually relevant responses. Various scenarios can be considered, including knowledge retrieval, decision support, automation of simple tasks or complex business processes, proactive assistance, and generating synthesis-based knowledge—especially when the source of synthesis is a limited dataset. Realizing the potential of integrating context-aware VAs with enterprise service platforms entails structuring the context surrounding specified activities—such as knowledge-gathering, operating-support, or knowledge-synthesis tasks.

4. Functional Capabilities and Use Cases

Context-Aware Virtual Assistants (CAVAs) equipped with proactive semantic analysis and task automation capabilities address two distinct problem areas that hinder efficiency and productivity in large organizations: the time-consuming nature of information retrieval and the tediousness of repetitive tasks. In such environments, an increasing burden rests on employees' capacity to absorb, apply, and share knowledge, contributing to knowledge overload. CAVAs alleviate these difficulties by synthesizing information and automating processes, augmenting human capabilities rather than replacing them.

CAVAs offer core functionality similar to existing knowledge assistants but set themselves apart through real-time monitoring of systems and user activities. Continuous semantic analysis identifies inflection points that present opportunities for automation or decision support. Activities with a repetitive nature, in which the contextual information being acted upon reflects a pattern already established, allow for automation of the corresponding behavior. In contexts characterized by uncertainty, CAVAs assist in narrowing down the possible alternatives.

Equation B. Explicit context retrieval + implicit filtering

Let services be $s \in \mathcal{S}$.

Step 1 — initial retrieval score using explicit context

$$\mathrm{Score}_{\mathrm{exp}}(s) = \mathrm{sim}\big(\mathrm{query,service}(s)\big) \cdot g\big(\mathbf{c}_{\mathrm{explicit}}\big)$$

- sim: text/semantic similarity
- $g(\cdot)$: boosts/filters based on explicit context (role, department, locale, etc.)

Step 2 — implicit-context filter / re-ranker

$$\mathrm{Score}(s) = \mathrm{Score}_{\mathrm{exp}}(s) \cdot f\big(\mathbf{c}_{\mathrm{implicit}}\big)$$

where $f(\cdot) \in [0,1]$ down-weights items that don't fit implicit constraints (current workflow stage, recent actions, platform signals), exactly as described.

Step 3 — selecting top-k

$$\mathcal{S}_k = \mathrm{TopK}_{s \in \mathcal{S}} \mathrm{Score}(s)$$

Step 4 — correlating partial results to synthesize one response
If multiple services return partial results $r_1, r_2, \dots, r_m$, the paper says the "formal context model correlates incoming partial results and generates a unified response."
A standard formalization:

$$\mathrm{Answer} = \mathrm{Synthesize}\big(r_1, \dots, r_m \mid \hat{\mathbf{c}}(t)\big)$$

4.1. Knowledge retrieval and synthesis

The use of a context-aware virtual assistant to facilitate knowledge retrieval and synthesis showcases how these systems can enhance the user experience within an enterprise service platform. An enterprise service platform is a collection of services (and associated data) made available within an enterprise domain that can be accessible and reused by other services to support business processes across organizational boundaries. In this case, the enterprise service platform implements the services offered by a department responsible for managing corporate travel, accounting, and human resources. These services cover a variety of functions that satisfy the requests of employees and comply with legislation, and therefore any request requires the involvement of multiple actors or partners. A key feature of the service platform is its open nature, making it possible to add services offered by partners outside the organization to enhance the services used by employees. In a corporate travel service, for example, the agent manages the internal aspects of the service and uses external service providers—airline companies, hotel chains, car rental companies, insurance companies, and so on—to satisfy the client's request. To support automated queries about these services, a context-aware virtual assistant is positioned as an intermediary between employees and the enterprise service platform's services.

When a user query is made, explicit context is used to retrieve the most relevant services for the task. An additional context-based filtering step enhances the results by analysing implicit information, which can be made available by the enterprise service platform. This kind of context-aware approach has the advantage of using context as the main parameter not only to retrieve the most relevant information from the data sources but also to check the suitability of the sources at execution time. Finally, when the context-aware virtual assistant is used to fulfil complex user requests that require the retrieval of information from multiple services to respond correctly, the formal context model is applied to correlate incoming partial results and generate a unified response to the user.

Table 2. Itemized Contribution Scores for Context-Aware Knowledge Synthesis Evaluation

Item (1–10)	Raw score (1–5)	Contribution
1	4	3
2	2	3
3	5	4
4	2	3
5	4	3
6	1	4
7	5	4

4.2. Task automation and decision support

Large-scale enterprise systems often require humans to perform routine and time-consuming tasks to fulfil business operations. These sessions involve repeated actions or structured workflows. A context-aware VA with sufficient authority can undertake these tasks on behalf of users to improve productivity. In addition to automation, step-by-step assistance is also available. For example, it can assist users by automating the execution of repeated functions, suggesting the next steps to minimize user cognitive effort, or checking and validating the correctness of an assigned task with well-defined requirements. In this sense, it acts as an AI-enabled, automated consultant that considers every relevant facet.

Context-aware VAs can identify the execution status of such tasks or workflows and notify users of anomalies or exceptions. For instance, if a user inquires about a specific task but has not yet received any notification about completion within the usual execution duration, the VA can check the progress. Depending on the user request, it can find the responsible user group, check the execution status of the task, notify the responsible user of the delay, escalate it to the next level of management, or even notify the end-user of the task's failure and offer possible alternatives. In addition, a context-aware VA can suggest, initiate, or evaluate a complex decision according to a specific context.

5. Privacy, Security, and Compliance

When enriching enterprise service platforms with context-aware virtual assistants, the privacy and security of user data, including sensitive organizational data as well as personally identifiable information of the employees, should be given utmost importance. Therefore, mechanisms must be incorporated to ensure the protection of user privacy and prevent the leakage of sensitive corporate data throughout the VA pipeline.

A comprehensive data governance framework must also be established, encompassing the definition and enforcement of data authorization and access control policies for the data stored within the enterprise service platform. Such policies should dictate which data may be used for training the VA model, under what conditions data sharing is permitted, and who is authorized to access which data items. This will guarantee that in data-sensitive situations, such as when a user interacts with the VA in a public place or when the underlying model is being shared with third parties, the VA is able to respect the users' privacy and the organization's data governance framework. A unified definition of the authorization and access policies for the complete data stored in the enterprise service platform will also help prevent friction and controversies while using the VA, enabling cooperation and boosting adoption.

To address privacy concerns on the data used to train the VA model, privacy-preserving techniques, such as federated learning, can be applied. By enabling the VA model to be trained over decentralized data sources that remain within users' control and are not shared with an external party, the risk of privacy leakage is mitigated.

5.1. Data governance and access control

Data governance describes the overall management of the availability, usability, integrity, and security of data. In the context of context-aware virtual assistants (CAVAs), sensitive information is inherently used by such systems to tailor their behavior during interaction. Cybersecurity concerns in the tailoring process are primarily associated with data access control and disclosure, and the following guidelines establish a conceptual framework that CAVAs should implement regarding access control:

1. The implementation of an access control mechanism is critical for CAVAs to mitigate privacy and security risks.

2. All sets of user context attributes must have access control policies associated with them.

3. Since the assistant is also a service platform, policies can be set by the administrator or by each user/machine/service.

4. If secret data exist in the user attributes, the user must be informed when it is being used by the current response, in order to authorize this access.

5. Access control must be applied only when disclosure is possible, meaning that when the visited/originating context is in fact a machine or service the disclosure condition should be ignored.

6. Access control must be applied before data protection or anonymization, e.g. an attribute must be confidential before being anonymized.

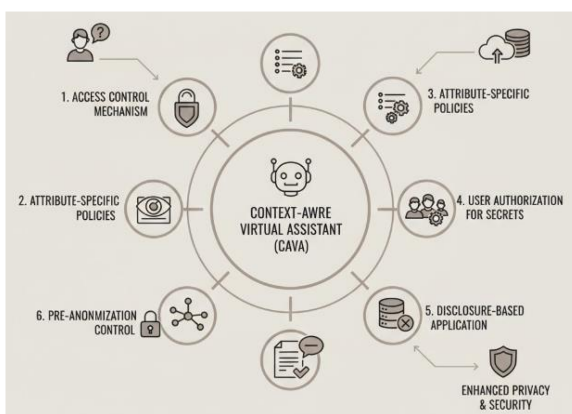

Fig 4: Securing Personalization: A Governance Framework for Attribute-Level Access Control in Context-Aware Virtual Assistants (CAVAs)

5.2. Privacy-preserving techniques

The integrity of personally identifiable information (PII) is vital for context-aware virtual assistants (CAVAs) to be trustworthy platforms. As CAVAs such as ChatGPT become increasingly capable, users are encouraged to share sensitive personal information with the platforms to improve service quality. However, such sensitive information may still be recorded when performing various tasks and could later be exploited for profit by malicious entities. To mitigate such risks, privacy-preserving techniques can alter identifiable data before being disclosed. In the context of a virtual assistant built with ChatGPT, such techniques can be applied to Zoom chats, email messages or even user tasks to prevent traceability and de-identification of personal data.

The concept of data anonymization is centered on the area of de-identification. De-identification covers any process that prevents the association of a specific user with any data. The term comprises two subcategories: anonymization and pseudonymization. Anonymization transforms data so that information cannot be reversed for any users. In its strictest sense, this means that the majority of unique user profiles in a dataset cannot be re-identified, regardless of the strength of background knowledge or of the technology available. Pseudonymization applies a reversible transformation so that the inverse procedure allows for the restoration of identifiable information. Tokenization additionally applies a high-control mechanism so that only a small group of powerful actors can restore sensitive data.

6. Evaluation and Metrics

The performance of context-aware VAs is determined by a range of metrics. Speed of response and prediction accuracy are among the most frequently studied quality-related measures for context-aware systems, particularly when these components rely on machine learning techniques. Another factor closely correlated with prediction accuracy is the temporal resolution of the data used as input: prediction errors generally increase as the time in the future for which a value needs to be forecasted also increases. Synchronous control is another area which impacts the satisficing of specific user needs: results show that the accuracy of synchronous control improves as communication latency decreases, while the accuracy of predictive control is improved by a longer response time.

Metrics related to user satisfaction and adoptability of context-aware capabilities represent another important category of performance evaluation. In the context of mobile and networked applications, besides performance criteria, such as response time, it is factors such as perceived usefulness, perceived ease of use and satisfaction that have a strong influence on both user intention to use the application and actual usage behavior. Specifically, perceived usefulness is defined as the degree to which a person believes that using the application will enhance his/her job performance while perceived ease of use is defined as the degree to which a person believes that using the application will be free of effort. Several applications are used as the basis for investigating the relationship among these constructs and user intention to use and actual use behavior; the results support the influence of perceived usefulness and perceived ease of use on user intention to use the application as well as that between user intention and actual use behavior. These findings indicate that VAs able to provide real-time responses to requests in a manner that is convenient for the user and without the need for additional help in their operation are perceived as useful and contribute positively to the overall usability of the systems.

Equation C. Privacy / access-control rules as a policy function

Step 1 — define an attribute-level policy decision
Let:

- user u
- requested attribute a (context attribute)
- requesting component k (VA module/service)
- situation/context $\hat{\mathbf{c}}(\mathrm{t})$

Policy decision:

$$\mathrm{Permit}(\mathrm{u},\mathrm{a},\mathrm{k},\hat{\mathbf{c}}) = \begin{cases} 1 & \text{if policy says allow} \\ 0 & \text{otherwise} \end{cases}$$

Step 2 — disclosure condition (guideline 5)
Only enforce disclosure controls when disclosure is possible:

$$\text{IfDisclosurePossible} = \mathbb{1}[\text{output is human-visible or externally shared}]$$

Then:

$$\text{Enforce} = \text{IfDisclosurePossible} \cdot (1 - \text{Permit})$$

Step 3 — user notification when secret data used (guideline 4)
Let $\text{Secret}(a) = 1$ if attribute is secret. Then:

$$\text{NotifyUser} = \mathbb{1}[\text{Secret}(a) = 1 \wedge \text{attribute used in response}]$$

6.1. Performance and accuracy

Performance and accuracy are key evaluation criteria, as context-aware virtual assistants (CAVAs) are often regarded as "intelligent" entities that should therefore produce correct result when responding to user queries. Context-aware factors may affect correctness; for example, the contextual information may be incomplete or inconsistent. Nevertheless, performance remains paramount for applications such as enterprise service request fulfilment. CAVAs should have low response latency, even during peak traffic periods, so that they do not become a bottleneck in any system. Continuous integration, deployment, and monitoring approaches can facilitate such requirements. In addition to being responsive, CAVAs should rapidly adapt their behaviour to fluctuating workloads.

Generally trained with external knowledge bases, the results provided from internal knowledge-bound queries are the most accurate. Knowledge retrieval quality should also increase as the knowledge base expands. Context retrieval delay determines the speed of agent-based query resolution, but CAVA response time should also consider the switching latencies introduced by the task-monitoring framework. During user query answering, high-context-awareness complements third-party service, knowledge base, and CAVA query results. In this context, CAVAs can be deemed accurate both qualitatively and quantitatively. An accuracy,self-learning feedback mechanism—which can be automatic or administrator-managed—and the increasing business transaction volume foster knowledge growth—is vital for continuous learning.

Table 3. System Usability Scale (SUS) Score Calculation Summary

Step	Value
Sum contributions	34.0
Multiply by 2.5	85.0
SUS score (0–100)	85.0

6.2. User satisfaction and adoptability

The user-centered nature of context-aware virtual assistants cannot be overstated. As a result, the usability of a prototype often makes it the centerpiece of an evaluation effort. Usability is defined as the extent to which users can achieve specific goals with the prototype effectively, efficiently, and in a satisfactory manner in a specific context of use. Measures of user satisfaction assess both the overall impression of the prototype and the acceptability of specific interactions, such as disappointment with missing answers. To avoid the pitfalls and biases of single-question Likert-scales, Cooper and Reimann suggested using questionnaires developed by the System Usability Scale (SUS)—a simple 10-item scale giving a global view on subjective assessments of usability.

SUS did not target any specific technology and therefore measures usability in a broad sense. Recent studies demonstrated its effectiveness in evaluating context-aware systems, being sensitive enough to detect differences among their variants. The mean score in a SUS test should be greater than 68; moreover, SUS performance can be assessed through a single graph that reports results of 20 reviews for the system under test and 100 systems in the SWEET database. The Net Promoter Score (NPS)—an index that measures the willingness of users to recommend a product to others—could also be employed to evaluate the experience of working with a VA by asking users to rate the probability of recommending the assistant to others on a 0 to 10 scale.

Adoption is also a key element in the success or failure of any technology. A prototype's continuity and adoption are determined by long-term users and their satisfaction, safely guaranteeing the completion of a task and the correctness of a decision—with context awareness improving the user experience. Hence, methods focusing on the formulated task can also be employed to gauge adoptability. In particular, the Delone and McLean Information System Success Model has been successfully applied on a number of context-aware systems.

7. Conclusion

To summarize, although various attempts have been made to develop context-aware virtual assistants for embedding in enterprise service platforms, such initiatives have not been sufficiently investigated. Context-aware virtual assistants enable context-aware information retrieval and information synthesis. In addition, they support the automation of contextually simple, repetitive tasks and offer contextual advice for complex tasks requiring additional cognitive demands. The above functions are supported by synthesizing various context-aware capabilities, including context-aware knowledge retrieval, context-aware task automation, and context-aware decision support.

The proposed concepts and models lay the foundation for building context-aware virtual assistants. Future research will focus on developing an integrated system that leverages context-aware information and processes for deploying enterprise service platforms in a context-aware manner. Insights and evidence from real deployments and user acceptability studies will further refine the set of context-aware techniques and services for embedding into enterprise service platforms.

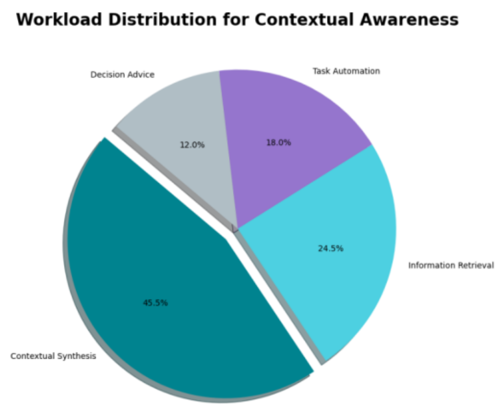

Fig 5: Workload Distribution for Contextual Awareness

7.1. Final Thoughts and Future Directions

Enterprise Knowledge Management has reached a turning point. Globalization, Artificial Intelligence, big data technologies, and their management have transformed the nature of all services and products. The evolution from goods-based industries toward services-and-knowledge-based industries has changed how an enterprise maintains and operates its knowledge. Knowledge becomes fluid, and the innovative process of knowledge management accelerates. Collaborative platforms that provide Context-Aware Virtual Assistants result from these modifications. Context-aware technology can be seen as a response to the need for establishing Context-Aware Virtual Assistants in Knowledge Management processes on collaborative enterprise service platforms.

Recent advancements in the fields of knowledge management, artificial intelligence, and context-awareness technologies are providing new sustainable means for implementing efficient and effective knowledge management processes in organizations and innovative enterprises. These areas can be integrated to create collaborative enterprise service platforms that allow Context-Aware Virtual Assistants to dynamically provide appropriate knowledge to the right people at the right time, through the right channel, and in the right form, based on real contextual information. Researchers and practitioners can then leverage the advantages of these platforms to address or at least alleviate the challenges hindering successful knowledge management. Context-awareness technologies allow collaborative enterprise service platforms to dynamically process Context-Aware Virtual Assistants, which are intelligent knowledge service agents that deliver knowledge in a context-sensitive manner.

8. References

[1] Abowd, G. D., Dey, A. K., Brown, P. J., Davies, N., Smith, M., & Steggles, P. (1999). Towards a better understanding of context and context-awareness. In Proceedings of the 1st International Symposium on Handheld and Ubiquitous Computing (pp. 304–307). Springer.

[2] Avinash Reddy Segireddy. (2022). Terraform and Ansible in Building Resilient Cloud-Native Payment Architectures. International Journal of Intelligent Systems and Applications in Engineering, 10(3s), 444–455. Retrieved from https://www.ijisae.org/index.php/IJISAE/article/view/7905.

[3] Anwar, A., & Li, W. (2020). A survey of federated learning in edge computing: Methodologies and applications. IEEE Access, 8, 140843–140865.

[4] Amistapuram, K. (2022). Fraud Detection and Risk Modeling in Insurance: Early Adoption of Machine Learning in Claims Processing. Available at SSRN 5741982.

[5] Bardram, J. E. (2005). Activity-based computing: Support for mobility and collaboration in ubiquitous computing. Personal and Ubiquitous Computing, 9(5), 312–322.

[6] Rongali, S. K. (2022). AI-Driven Automation in Healthcare Claims and EHR Processing Using MuleSoft and Machine Learning Pipelines. Available at SSRN 5763022.

[7] Bast, H., Buchhold, B., & Haussmann, E. (2016). Semantic search on text and knowledge bases. Foundations and Trends in Information Retrieval, 10(2–3), 119–271.

[8] Varri, D. B. S. (2022). AI-Driven Risk Assessment and Compliance Automation in Multi-Cloud Environments. Available at SSRN 5774924.

[9] Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623.

[10] Vadisetty, R., Polamarasetti, A., Guntupalli, R., Rongali, S. K., Raghunath, V., Jyothi, V. K., & Kudithipudi, K. (2021). Legal and Ethical Considerations for Hosting GenAI on the Cloud. International Journal of AI, BigData, Computational and Management Studies, 2(2), 28-34.

[11] Berners-Lee, T., Hendler, J., & Lassila, O. (2001). The semantic web. Scientific American, 284(5), 34–43.

[12] Gottimukkala, V. R. R. (2022). Licensing Innovation in the Financial Messaging Ecosystem: Business Models and Global Compliance Impact. International Journal of Scientific Research and Modern Technology, 1(12), 177-186.

[13] Bhutani, N., Zheng, X., & Jagadish, H. V. (2020). Learning to inject knowledge into language generation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (pp. 3469–3479). Association for Computational Linguistics.

[14] Aitha, A. R. (2021). Dev Ops Driven Digital Transformation: Accelerating Innovation In The Insurance Industry. Available at SSRN 5622190.

[15] Bolchini, C., Curino, C. A., Quintarelli, E., Schreiber, F. A., & Tanca, L. (2007). A data-oriented survey of context models. SIGMOD Record, 36(4), 19–26.

[16] Nagabhyru, K. C. (2022). Bridging Traditional ETL Pipelines with AI Enhanced Data Workflows: Foundations of Intelligent Automation in Data Engineering. Available at SSRN 5505199.

[17] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.

[18] Garapati, R. S. (2022). AI-Augmented Virtual Health Assistant: A Web-Based Solution for Personalized Medication Management and Patient Engagement. Available at SSRN 5639650.

[19] Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., … Amodei, D. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901.

[20] Inala, R. (2020). Big Data-Driven Optimization of Retirement Solutions: Integrating Data Governance and AI for Secure Policy Management. Global Research Development (GRD) ISSN: 2455-5703, 5(12).

[21] Byun, H. E., & Cheverst, K. (2004). Utilizing context history to provide dynamic adaptations. Applied Artificial Intelligence, 18(6), 533–548.

[22] Meda, R. (2020). Data Engineering Architectures for Real-Time Quality Monitoring in Paint Production Lines. International Journal Of Engineering And Computer Science, 9(12).

[23] Carbonell, J., & Goldstein, J. (1998). The use of MMR, diversity-based reranking for reordering documents and producing summaries. In Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 335–336). ACM.

[24] Sheelam, G. K., & Nandan, B. P. (2022). Integrating AI And Data Engineering For Intelligent Semiconductor Chip Design And Optimization. Migration Letters, 19, 2178-2207.

[25] Chen, H., Finin, T., & Joshi, A. (2003). An ontology for context-aware pervasive computing environments. Knowledge Engineering Review, 18(3), 197–207.

[26] Kummari, D. N. (2021). A Framework for Risk-Based Auditing in Intelligent Manufacturing Infrastructures. International Journal on Recent and Innovation Trends in Computing and Communication, 9(12), 245-262.

[27] Chowdhery, A., Narang, S., Devlin, J., Bosma, M., Mishra, G., Roberts, A., … Fiedel, N. (2022). PaLM: Scaling language modeling with pathways. arXiv.

[28] Cook, D. J., Augusto, J. C., & Jakkula, V. R. (2009). Ambient intelligence: Technologies, applications, and opportunities. Pervasive and Mobile Computing, 5(4), 277–298.

[29] Cooper, A., Reimann, R., Cronin, D., & Noessel, C. (2014). About face: The essentials of interaction design (4th ed.). Wiley.

[30] Pandiri, L. The Future of Commercial Insurance: Integrating AI Technologies for Small Business Risk Profiling. International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE), DOI, 10.

[31] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

[32] DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. Journal of Management Information Systems, 19(4), 9–30.

[33] Annapareddy, V. N. (2022). Integrating AI, Machine Learning, and Cloud Computing to Drive Innovation in Renewable Energy Systems and Education Technology Solutions. Available at SSRN 5240116.

[34] Dey, A. K., Abowd, G. D., & Salber, D. (2001). A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications. Human–Computer Interaction, 16(2–4), 97–166.