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Contextualization of Information Objects Towards Supporting Knowledge Management in Digital Workspaces

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Abstract. This research article explores the contextualization of information objects in enhancing knowledge management within digital workspaces. It emphasizes the critical role of context in managing unstructured data and presents a systematic approach for extracting context dimensions and attributes for information object context modeling. The research article discusses several implications of context-aware computing for organizational productivity: efficient information retrieval, improved knowledge management, support for remote and hybrid work models, reduced data loss, enhanced user activities, and business-level services. The article emphasizes the CASAD matrix modeling method and proposes the approach of extracting the set of attributes for building a context model. A case study is presented to demonstrate the practical application of this approach in an organizational setting. It is shown how combining large language models (LLMs) and organization-specific metamodels contributes to computing secondary context attributes. The research concludes that contextualizing information objects, supported by artificial intelligence and LLMs, can enhance organizational productivity by providing a ground for personalized digital workspaces, efficient information handling, and improved knowledge management processes. It can also support the evolving needs of organizations, such as remote and hybrid work models.
Keywords: Context-Aware Computing, Context Modeling, Context Attributes, Organizational Knowledge Management, Personalized Digital Workspace, Artificial Intelligence, Large Language Models.

1 Introduction

The steadily increasing number of business applications within organizations results in a large volume of unstructured data, making analysis and search tasks cumbersome and time-consuming. According to Gartner, unstructured data represents an estimated 80 to 90 percent of all new

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enterprise data. Furthermore, it is growing three times faster than structured data. More precisely, it was predicted that the volume of unstructured data is set to grow from 33 zettabytes in 2018 to 175 zettabytes by 2025 [1]. The overwhelming increase in data generated from customer relationship management (CRM) systems, Enterprise Content Management (ECN) systems, e-mails, collaboration tools, and social media platforms [2] not only complicates retrieval but significantly impacts productivity, particularly in hybrid and remote work models. Valuable organizational data may be misplaced, requiring additional resources to locate it, highlighting the need for mechanisms to store and efficiently retrieve it when needed [3]. Another risk is the inadequate control over information containing personally identifiable data due to poor information management.

Given these circumstances, it is becoming increasingly important for organizations to establish robust knowledge management systems. These systems should leverage artificial intelligence (AI) solutions and cognitive document management systems to exploit the untapped value of unstructured data and provide quicker access to necessary information [4].

With the rise of remote and hybrid work models, modern and employee-oriented knowledge management solutions within an organization's intranet have become essential for productive work. The research of [5] emphasizes the importance of communication, coordination, connection, and other aspects in knowledge-based hybrid work while [6] explores the challenges of knowledge management in a remote work environment. One of the solutions is improving the personal digital workspace. Digital workspace includes organizational strategy and technological means to knowledge exchange, productivity, and employee's creativity in the work environment [7]. In this article, a digital workspace is understood as a set of tools and virtual interaction spaces necessary to support the employee's work process, access to various types of significant work-related information, and communication within the organization and with the external environment. The inadequacy of organizing and personalizing the digital workspace is recognized as an untapped potential for digitalization, and currently, optimizing such work environments is one of the priority research directions [8].

Various information technology resources and their interactions allow for the collection of additional data on heterogeneous information objects in content and format – emails, documents, social media posts – subsequently performing automatic data analysis. Viewing this data in context is particularly important, as context (e.g., time, activity flow, content, location) directly improves work productivity and ensures organizational operations. Employees spend a significant portion of their work time searching for necessary information within organizational resources or manually contextualizing the acquired information before incorporating it into the desired workflow within the organization. The use of AI for automating this work is already being applied in various applications [9], [10].

The use of AI for knowledge management tasks is already an explored area [11]. However, the evolving capabilities and application methods of AI, along with changes in corporate operations, communication channels, information volume, and automation capacities, underscore the growing importance and potential of AI in corporate knowledge management.

Enhancing information objects with context from both metadata and semantically defined information from various data sources can facilitate information retrieval, availability, and reaching the appropriate recipient more quickly and with fewer resources. For instance, a contextually enriched document can be used for routing and determining information flow, delivering the appropriate information to the relevant employee, or for more targeted information retrieval within the intranet on demand, i.e., retrieving a more contextually suitable set of results for the employee's search. Studies demonstrate that the use of contextual information in recommendation systems and mobile applications significantly improves user productivity [9], [10]. However, there are not enough studies identifying the importance of various types of contextual information and the context analysis of heterogeneous information sources in the company's information flow. Despite advancements in AI and machine learning, existing knowledge management systems lack the ability to adequately contextualize data for efficient retrieval.

Our research aims to propose a different approach to context-aware computing within knowledge management systems, focusing on the CASAD matrix method for extracting context attributes. Unlike traditional AI-based systems that often rely on surface-level data, our method leverages a combination of primary and secondary context attributes, incorporating both user-generated and metamodel-based data. By contextualizing information objects within a digital workspace, we aim to improve the efficiency of knowledge management processes, particularly in environments characterized by remote or hybrid work models.

The research methodology is briefly discussed in Section 2. Sections 3 and 4 represent the essence of current research in context-aware systems with an emphasis on knowledge management processes and corresponding context types, while Sections 5 and 6 elaborate a practical approach for the enrichment of the company's information objects from the perspective of contextualization.

2 Research Methodology

This study contributes to developing a systematic approach to extracting context dimensions and attributes as the key means for information object context modeling, resulting in knowledge management support. To implement the proposed approach, a prototype for a digital workspace solution operating in a cloud service environment is to be developed. This prototype will provide technical means and functionality for collecting information objects from data sources, storing and processing documents, generating and enhancing metadata, and visualizing data at the user interface level for a personalized user workspace. The digital workspace will serve as a centralized knowledge and information hub for each organizational role and include the main features as shown in Figure 1.

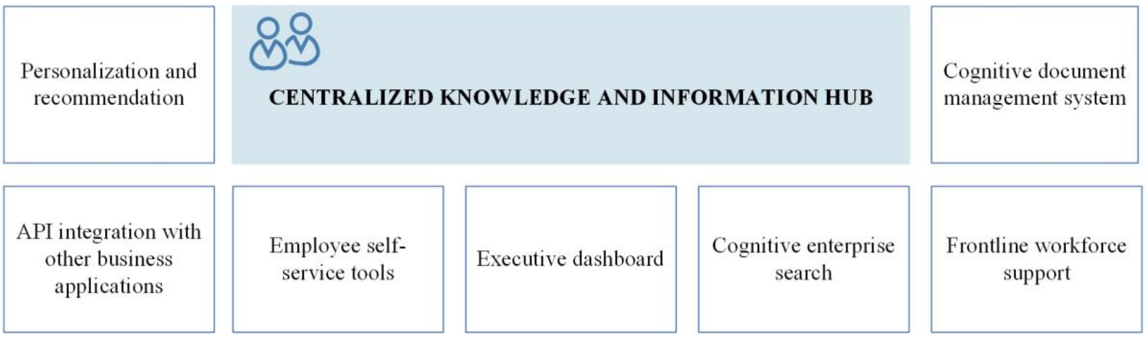

Figure 1. The outlook of a digital workspace

Contextualization is related to implementing context-aware computation solutions; it allows for simpler and more meaningful information storage [12]. To develop an approach for contextualization of information objects within a digital workspace environment, a systematic methodology, consisting of a literature review and consecutive experimental design was applied.

An iterative approach based on the snowballing technique was used (modified from [13]) to select the studies necessary for context dimension, attribute, and context modeling research. In the first step, the overview papers were identified using combinations of keywords *context-aware AND review OR survey*. The sources were limited to scientific paper databases IEEE Xplore, ScienceDirect, and SCOPUS. These three databases cover a significant portion of published papers. Based on the publication date, the quality of the papers, and the concepts to review, further elimination criteria and keyword sets were formulated. The following papers were excluded:

- studies that are not in English;
- studies published earlier than 2018 except when no later publications exist in the related field;

- studies that use the term “context analysis” in a narrow sense that is also not related to context-aware computing (for example, in image processing, the term “context” is used to refer to pixel parameters acquired from an image);
- studies unrelated to computer systems, automation systems, or information systems.

The following keywords on domains with similar properties to document systems were included: context-aware AND (recommendation OR content delivery OR learning systems OR tutoring systems OR knowledge management OR information management).

Based on the findings and conclusions of the related work research, the approach for contextualizing information objects (presented in Section 5) was developed by supplementing approaches in the existing studies and then applied to contextualize the information objects of specific organizations, thus setting the basis for the digital workspace implementation.

3 The Role of Contextualization for Organizational Knowledge Management

Context-aware computing emerged in the 1990s, and this article, similar to other related studies (e.g., [9], [12]), uses a definition that interprets the context as information that can be used to describe the situation of an entity. In context-aware computing, “an entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves” [14]. A context model is used to implement computational tasks that benefit from the context information; a context model represents the subset of context that can be realistically obtained from the sensors, applications, and users. Context attribute is an element of the context model that describes the context. Context attribute has an identification, type, value, and optionally – a set of properties [12].

Context-aware computing is used for performing various tasks in systems that are considered to be ubiquitous computing systems or the components thereof – e.g., smart homes, personal assistants, and automation systems [9], [15]. Context awareness is expected as a general property in smart solutions, services, and products [16]. Typically, context-aware systems encompass research and technology areas that use a large amount of data and heterogeneous data sources – for instance, the Internet of Things or edge computing applications. It must also be considered that the sensors that serve as data sources can be physical and virtual [12]. This allows the use of context models in systems that contain heterogeneous virtual sensors or a combination of virtual and physical sensors – for instance, context-aware recommendation systems, context-aware tutoring systems, etc.

Context-aware computation methods are used in systems where the result can significantly differ based on the context information. According to the review paper [15], the most important areas for context-aware systems as services are industrial automation, the medical domain, transport and mobility, and assisted living. Context-aware systems are also used to tackle tasks related to emergencies [17] and to model personal assistants [9]. Each of these application domains contains a set of tasks that can be supported by context awareness, usually decision-making and support, prediction-making [12], [15], [17], but also such tasks as process and data management, resource (e.g., energy consumption) optimization, safety-related tasks, as well as enhancement of human-computer interface [15].

Although the architecture of context-aware systems in various application domains is similar, it significantly differs depending on data sources and properties and the information these systems obtain. However, the challenge that context-aware systems in all domains share is a large number of heterogeneous data sources [12], [15]. This means that various data fusion algorithms play a significant role in context analysis, as the data from different sensors might need to be fused to create context, which is why context attributes are usually organized in groups and by formats. In a technical implementation of context-aware systems for various domains, however, the algorithms used to transform data will vary depending on the sensor data.

Context-aware computing and, respectively, contextualization are extremely important in knowledge management, as they enhance the ability to provide the right knowledge at the right time, tailored to the user's needs, environment, and tasks. Context-aware computing is vital to effective knowledge management by improving the relevance of information, enhancing decision-making, supporting personalization, facilitating efficient knowledge sharing, and increasing knowledge discovery [4], [18]. In knowledge management systems, similar to context-aware tutoring systems, there is a large amount of virtual data sources, which means that there are either no physical sensors. Instead, data is obtained from the information system or directly from the users. On the one hand, that means that there is one abstraction layer (physical layer) less when compared to, e.g., automation systems, yet at the same time, there are additional challenges. In particular, in knowledge management systems, data generation depends on a human [19]. The data obtained automatically from personal assistants or social network applications can be considered objective; for instance, usage habits can be quantified and measured [9]. However, in knowledge management systems, data depends on a user-sustained work environment. This means that the data sources are heterogeneous, virtual, and subjective. So, special attention must be paid to data interpretation and how data may depend on the role and functions of a particular employee in an organization.

The function of the context in knowledge management systems is also important as it is related to the tasks performed by knowledge management systems. A reference architecture for knowledge management systems identifying the context as an essential part of knowledge management systems has already been proposed two decades ago [20]. There are some models that include personalization or context modeling specifically for knowledge management systems [21]. The use of context information is particularly stressed in developing proactive knowledge management systems [19], among other knowledge management process support [22], as summarized in Table 1. Although there is a small number of context-aware knowledge management solutions in the literature, context-aware content recommenders and personal assistants have similar properties and tasks to solve [9], as these solutions also contain virtual sensors and information sources.

Table 1. Knowledge management process and context-aware solution mapping

Knowledge management processes [22]	**Context processes [12]**	**The function supported by context**
Knowledge creation/capture	Execution	Decision-making support [15] and prediction [23]
Knowledge filtering/selection	Execution, presentation	User experience support [24], content delivery [25], context-aware recommendation systems [9]
Knowledge codification	Tagging	Context tagging for rule acquisition [12]
Knowledge refinement	Execution	Decision-making support [15]
Knowledge sharing	Execution, presentation	User experience support from a modeling perspective [15] and in a technical sense [26], in particular for proactive knowledge sharing
Knowledge access	Execution, presentation	Content delivery [25], context-aware recommendation systems [9], knowledge representation [27]
Knowledge learning	Execution, presentation	Intelligent tutoring system applications: process adaptation, content delivery [25]
Knowledge application	Execution, presentation	User experience support [24]
Knowledge evaluation	Execution	Decision-making support [15] and prediction [23]
Knowledge reuse	Tagging	Storing context structure [12]

The information sources used in the internal circulation of the information are heterogeneous in terms of content, language, and syntax. These information objects supply the employee's digital workspace with the necessary data. Contextualizing these information sources in the digital workspace would enable more productive circulation of the information and new applications, such as context-aware productivity measurements and improved client interaction.

In the literature, widely acknowledged classification for how the data obtained from the sensors may be used [12] is (1) presentation, when context data is used to improve human-computer interface; (2) execution of some specific services; (3) tagging, which essentially means extracting additional context parameters from the existing data. Based on these tasks, the analysis of context awareness in Internet of Things systems [12] and in context-aware systems as smart services [16] was performed. These tasks can also be used to define how context data can be used in knowledge management solutions.

Tagging is used for knowledge codification and reuse since context modeling allows the creation of knowledge structures and the use of them to acquire or use new rules. The remaining context processes are related to the support of a function: the functions supported by context awareness are acquired by mapping context-aware applications and knowledge management processes.

4 Analysis of Context Types

A context model has multiple definitions; this article defines it as a set of attributes used to obtain results related to the context. This, in turn, means that developing a context model is associated with developing a set of context attributes and choosing approaches to process this attribute set.

It has been stressed in multiple sources that due to the broad perspective of ubiquitous computing, choosing the context model and its components (i.e., attributes) is methodologically poorly supported [15] and subjective; it varies depending on the solution [12]. In addition to this methodological complexity, one must also consider that the data necessary for extracting the context information can be either incomplete or not accessible at all; the attributes that are available in some systems are not available in other systems or obtainable with similar albeit different sensors. For these reasons, from the process perspective, multiple studies [12], [16] acknowledge that context-aware solutions depend on a particular domain and the type of the systems; in practice, there is no abstract general context model even if the formal definition theoretically exists. Consequently, the development of context models is a process grounded in best practices, as extensively reviewed in the literature.

Four different processes are widely accepted to retrieve context and develop context models: context acquisition, context modeling, context reasoning, and context dissemination (Figure 2 – adapted from [12]). These processes form a general process model that is used to analyze different types of systems in the overviewed papers (e.g., [12]); the processes are also used to review models on a lower (implementation) level [16], to analyze smart services, i.e., context dissemination; [15] demonstrates, how this general process can be applied to various automation systems.

Context acquisition is related to context data acquisition; in practice, the attribute set must be defined to acquire the result [12]. *Context modeling* includes selecting the data structure that suits the application of the model for further use: for instance, ontologies, graphs, key-value pairs, and objects [12]. *Context reasoning* relates to applying the context for a particular task, creating a context-aware function or service [12], [28]. Finally, *context* dissemination is related to how the context model is explicitly used to support systems or users' functions. In the first stage of this research, the main focus was on acquiring the context, i.e., the selection of the attributes. However, as explained later, it cannot be entirely separated from the remaining process.

It is essential that the context can be primary or secondary, which means that primary or secondary attributes can be used to model context. Similar classifications of the attributes can be found in different sources under different terms, but the idea is as follows.

Primary context is acquired from the attributes where the values are obtained directly from the sensors. There are physical sensors, virtual sensors (e-mail and chat applications, calendars, contact lists, etc.), and logical sensors (i.e., sensors that perform some data processing [12]. Physical sensors are used when developing applications related to mobile devices [9], the Internet of Things [12], or biometric systems [29]. Virtual sensors are used, e.g., in recommendation systems [9] or intelligent tutoring systems [30] – besides, one system can contain both virtual and physical systems, depending on the system's goals and architecture.

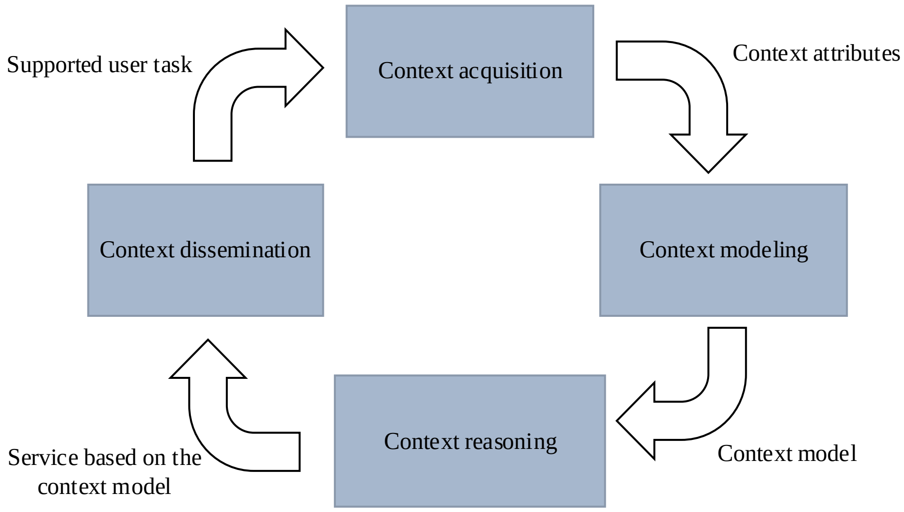

Figure 2. Context modeling process [12]

Secondary context is acquired by developing primary context attribute values using a model: algorithm, formula, or metamodel [12]. The values of the same attribute can be obtained either directly from the sensor (i.e., as the values of the primary attribute) or through a model (i.e., as the values of the secondary attribute). As a result, the same attribute content-wise can be primary or secondary in different models. Context data can be obtained in three different ways: directly from the sensor (i.e., primary context), deducted (i.e., secondary context), or obtained manually (usually the data obtained manually is statical throughout the operation of the system – e.g., user surveys; and can be either primary or secondary). Figure 3 shows how the context terms are related.

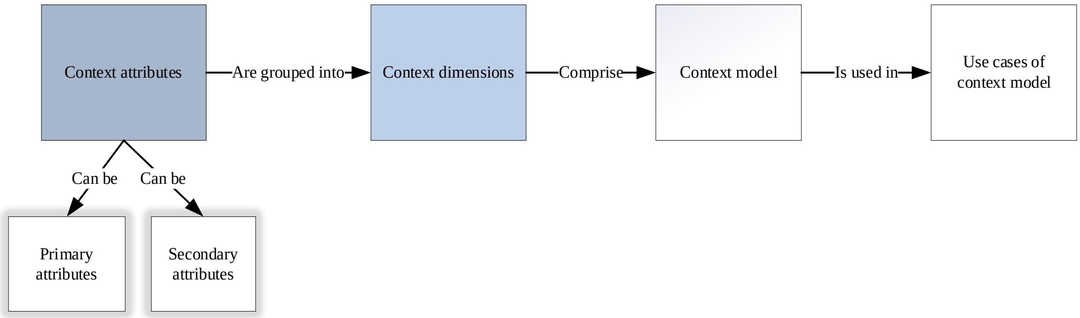

Figure 3. The relationship between context-related terms

Context can have multiple categories that depend on the classification, for instance, activity, temporal, identity, and spatial categories. However, these categories differ in various studies [12]. These categories are called context dimensions [9] and are closely related to the application domain. Even though, in theory, it is possible to define a general set of attributes, in practice, it will still depend on the application domain. The mathematical and conceptual definition of dimensions may vary depending on the methods used in context reasoning. Dimensions can be used to group attributes in sets or to put values on the same quantifiable axis. The context dimensions for various domains are displayed in Table 2.

When analyzing the structure of context-aware systems, one can see many dimensions, related attributes, and various context-aware system goals. Besides, the systems themselves are hierarchical and consist of many elements. As a result, the selection of context attributes and mapping them onto tasks is not trivial. There is a variety of design approaches intended to select a set of attributes and model the domain – there is no united methodological support; for this reason, system designers often use a systemic approach. A recent survey shows that because of this complexity, the contextual characteristics of systems are either completely ignored or the relationships between attributes and system functions are viewed superficially [35].

Table 2. Context dimensions

Context dimension [9], [10]	Related context attributes (sets are not finite)	Systems where dimensions are applied
User-dependent context	Interests	Used in tutoring and other systems where the user connects to individual profiles [30] Client service systems, recommendation systems Systems that adapt a particular process, e.g., working out, to a specific user [31]
	Goals	
	Emotions	
	General profile information	
Location/spatial context	Location in a more broad meaning (e.g., GPS coordinates), often mapped to time	Document analysis, data storage, tutoring systems
Social situation context	Interactions when performing specific tasks	Typically, in social networks [9], [25] In applications where social history is crucial, recommendation systems [26]
	Parameters specific to social networks – comments, reactions, tags	
	Similar interests (also similar roles, functions)	
Temporal/time context	Time in different granularities	Document analysis, data storage
Activity/functional context	Past or current activities	Typically used in mobile recommender systems [9]
	The similarity of previously performed activities [10]	Used if nothing is known about the user, e.g., [32]
Item-specific context	Video context attribute set	To improve device-to-device network performance [26] Improving systems security and fault tolerance [33]
	Sensor context attribute set	
	Device position or movement dynamics attributes	Used in biometric data or mobile systems
Specific model or system-strategy-related context	Tutoring module and motivation module attributes in intelligent tutoring systems.	Systems where it is necessary to adapt the system's functioning to various settings [34]

Therefore, the next section investigates the design approaches for context-aware system development and outlines the steps toward identifying context models.

5 An Approach for Identifying Information Objects' Context

To define context models for digital workspaces, it is essential to identify the context dimensions and the attributes characterizing information objects and activities these models are intended to support. We suggest an approach to facilitate this process.

5.1 Choosing a Method for Context Acquisition from the Problem Domain

As emphasized in Section 4, the identification of context dimensions and attributes is not a unified task for various problem domains. Many studies and overviews exist because of the variety, mainly in requirements engineering. These studies focus on developing systems with contextual characteristics rather than fully context-aware systems [16]. Several types of methodologies exist for context-aware system design: general frameworks, frameworks for designing specific data models, automated design approaches, and classical systems analysis modeling approaches.

The authors of the article propose that the selected design approach must hold the corresponding requirements to be practically applicable in the scope of contextual enrichment of information objects within an organization:

- Does not isolate the selection of attributes from the task to be performed;
- Does not offer to design a data structure only;
- Allows the formal selection of different attributes;
- Allows the analysis of the possible alternatives;
- It is relatively straightforward for all stakeholders to discuss.

Therefore, design approaches were examined, considering these characteristics, and the results are summarized in Table 3.

Frameworks for designing specific data models refer to methods that design systems associated with a specific data storage structure, such as ontologies or key-value stores [16]. The most significant limitation of these methods is the lack of modeling at an early stage, i.e., in selecting attributes; they instead focus on creating a model in an existing data set.

There are also classic model-driven and user-requirement-driven system analysis methods, such as uniform modeling notation (UML) based and use cases [16]. Several sources note the lack of standard extensions for UML and BPMN, which would allow for context-based functions to be clearly and transparently integrated into context-aware systems (e.g., [35]).

Various more complex general frameworks are used; they guide the creation of context-aware systems from requirement specification to implementation. The general frameworks can be specific to some applications, based on concept definition and then manual mapping [36], generic and not leading to specific system architecture [28], or detailed enough to enable formal modeling of context-aware systems [37].

Table 3. The summary of context-aware system design approaches

	General frameworks	**User-requirement-based systems analysis methods (e.g., UML-based)**	**Frameworks for designing specific data models**	**Automated design approaches**
Can be used at the initial stages of the design – before the data structure	+	+	Usually considers the data already available	Data is necessary
Attribute mapping to context-aware functions	+	Not always defined, no standards that allow mapping in context-aware systems	Usually not used	Usually, a model is created for a specific pre-defined function.
Independence of the context model structure	Depends on the selected model	+	Depends on the selected model	+
Relative straight-forwardness	Depends on the selected model	-	Depends on the selected model	Straight-forward, once it has been set up

A relatively new set of approaches is automated design methods that use machine learning models to automatically select required attributes for specific systems, e.g., manufacturing systems [38] or recommender systems [39]. However, these methods require sufficient amount of representative data to train the design algorithm.

The analysis shows that a general design method with an independent context model structure that is relatively easy to use during a modeling session with different stakeholders is necessary. Two methods, CIM-SIS and CASAD, were further analyzed.

The modeling method CIM-CSS [37] allows for the formal modeling of the system. It uses a four-layer modeling approach and gives formal descriptions of elements containing the context model and their transformations. The method considers the links between the components of the context model and the system's functions. However, a more detailed examination of the method led to the conclusion that it was too complex and intertangled for the initial modeling sessions and all stakeholder groups; it also required making assumptions by selecting each of the context attributes into one of the five predefined classes. These classes further impact the formal modeling of the system, and a sound rationale should be provided for many of the attributes belonging to one or the other class.

The CASAD matrix method [37] defines context-model-design-related concepts in three sets: (1) activities or user tasks to be supported, (2) services or functions that are enabled by context-aware features, and (3) context attributes. The method's main advantage is that it allows these three sets to be formally compared and mapped, thus defining the interconnectedness of various context model abstraction levels. It is also simple enough to use in the initial modeling session and explain to the stakeholders. The method is informal and easy to modify, both an advantage and a disadvantage; however, simple and flexible use is essential at this design stage; therefore, it is chosen as a method for context requirement acquisition from the problem domain.

5.2 Application of CASAD Matrix Modeling Method

A matrix modeling method was chosen to acquire the mappings between different context model-related element sets. These element sets should be elicited from stakeholders and organization's documentation and might not be aligned in practice. The challenge in case of creating a knowledge management context-aware solution is that the knowledge of functional roles is often tacit and stored within the employees at the organization. For this reason, it is important to create a modeling session rather than take a fully formal approach. During the modeling session, relevant stakeholders retrieved the attribute and the activity set, while the set of services, as well as metamodels and models to be used for transforming primary into secondary attributes, were obtained from the relevant body of research.

The method is built upon CASAD matrix modeling method but expands in the following two directions:

1. A set of services, context dimensions, and metamodels is defined specifically for knowledge management systems and is reusable.
2. A primary-secondary attribute matrix is introduced to evaluate the feasibility of attributes.

The approach of extracting the final set of attributes for building a context model is depicted in Figure 4. Identification of business needs and analysis of the organization's existing information infrastructure are initial tasks that can be run in parallel. Theoretical (or analytical) background for supporting knowledge management is carried out by our analysis and can be reused for other organizations. Further interactions allow enrichment and refining of the attribute set concerning activities and services the context model is expected to support. The flows with solid lines provide generic support as they are based on research, while interrupted lines and blocks are case-specific and denote activities that should be implemented in each domain. Numbers in the upper-left corner of the blocks denote the section in this article where the corresponding activity is detailed.

During the research-based activity – Knowledge management related study analysis – three sets were identified to be further reused for various modeling cases:

- Set of context dimensions;
- Set of context-related services;
- Set of metamodels.

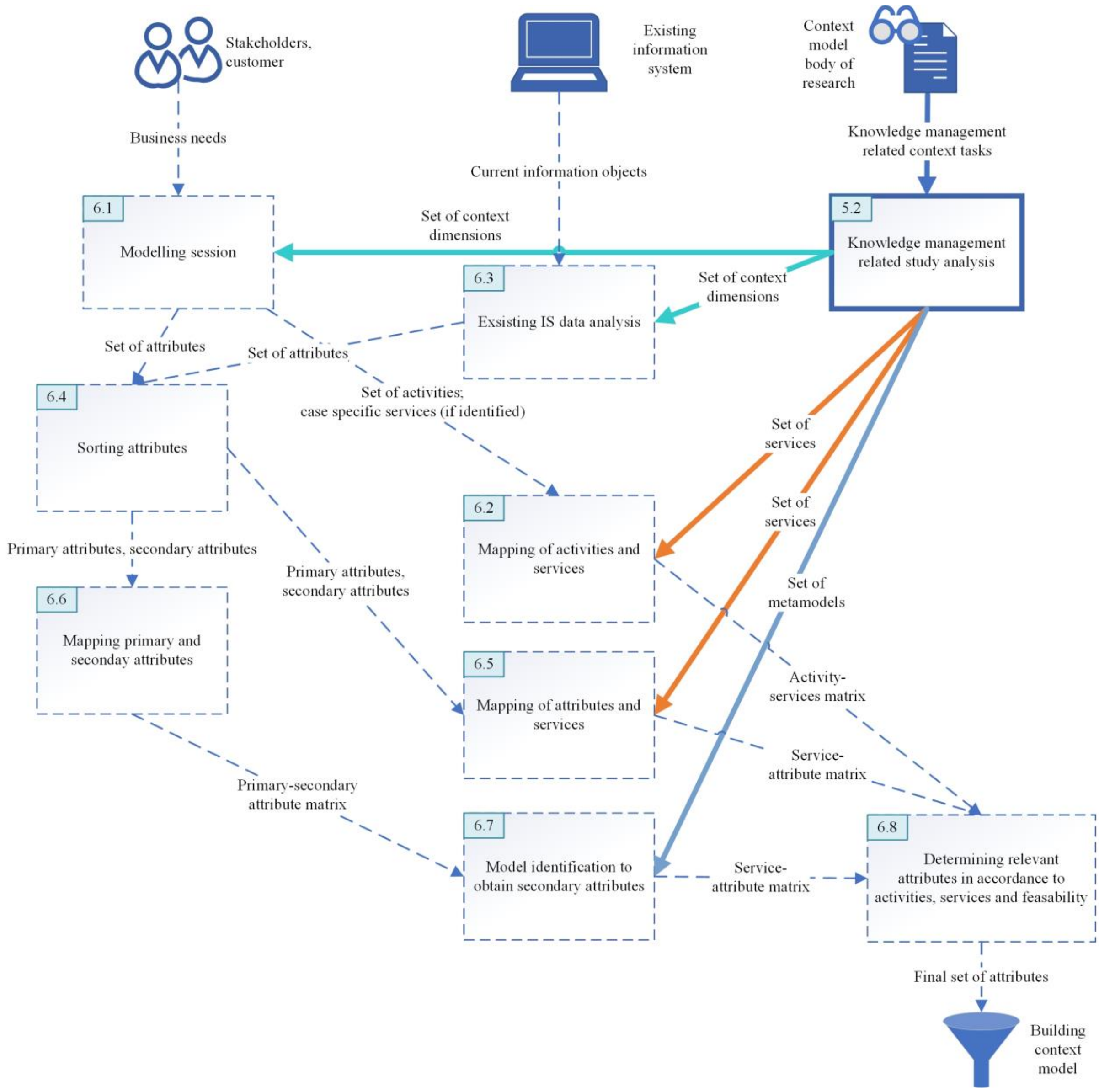

Figure 4. An approach for extracting a set of context attributes

Set of Dimensions

A set of dimensions, described in Section 4 and shown in Table 2, was used in an informal way to organize the IS analysis, as well as to guide the modeling session.

Set of Services

Tasks for specific context models were identified in the relevant body of research to define a set of services; this set can be also supplemented and confirmed during the modeling session as it is not finite. As this article aims to show the modeling part of the system related to context awareness, services associated only with context-aware systems are selected here. Three service groups have been identified as priorities describing various support scopes: business level (S3), user activities (S2), or system operation and functioning (S1); these groups are derived from literature analysis of contextual applications related to knowledge management support and general contextual systems. The services are mapped to the groups and have codes attached in Table 4. Some services correspond to two groups as they can support both the user's work and the business as a whole.

Table 4. Set of services

Title of the service	Service ID	Services related to system operation and safety (S1)	Services related to user activities (S2)	Services related to business level (S3)
Classification of current users	S1.1.	x		
Improving the system's performance (e.g., determining what to cash)	S1.2.	x		
Adapting the system's performance to various functioning modes	S1.3.	x		
Support of HCI performance	S1.4.	x		
Support of HCI functions	S2.1.		x	
Displaying information objects	S2.2.		x	
Classification based on criticality	S2.3.		x	x
Context-aware queries for ordering	S2.4.		x	
Context-aware queries for search	S2.5.		x	
Context-aware content delivery	S2.6.		x	
Identification of similar information objects	S2.7.		x	x
Delivering recommendations	S2.8.		x	
Deriving business rules for business process analysis	S3.1.			x
Prediction	S3.2.			x
Delivering recommendations for decision support	S3.3.			x
Storing knowledge	S3.4.			x

Set of Metamodels

A set of metamodels was defined based on the various fields of connection and can be broadly divided into three categories.

First, there are models related to the business for which the solution is being developed; some already exist, and some need to be created specifically for the context model. Classic systems analysis techniques such as expert interviews or document research can be used to obtain these models. Some metamodels, such as the organizational structure hierarchy, can be retrieved at least partially from existing information systems. There are the following metamodels related to business:

- The organization's business process model can be used for a variety of purposes;
- Ontologies or metamodels of the organization's activities and projects;
- Organizational structure (hierarchy);
- Ontology or dictionary of information object classes;
- Interpretation model for defining incoming and outgoing documents.

Secondly, there are models related to the organization's information system, which are also available through that system.

- Shared data metamodel – the access rights for different folders from which access rights for each document can be retrieved.
- User groups metamodel – different groups of users within an organization that can be obtained, such as MS Teams groups and e-mail lists.

Thirdly, these are the models for processing primary data. These models can be artificial intelligence models and algorithms or statistical models:

- Model for language analysis – such as LLM to process text;
- Other text analysis models that determine the frequency of term usage, such as the LDA (Latent Dirichlet Allocation) model.

The rest of the steps in the proposed approach are case-specific and shall be applied in a particular organizational context. A demonstration of applying them is given in Section 6.

6 An Example of Context Modeling Towards Personalized Digital Workspace

Application of the proposed approach is done on SME–agricultural cooperative which collaborates with a large number of different national and international organizations in its day-to-day work, providing a variety of services, from which it is apparent that the organization's processes are sufficiently complex and diverse. For example, export transactions, purchases of raw materials, insurance, storage and logistics services, production and marketing, which consequently also create diversity between involved information objects. The range of organization's systems consists of both ready-built and custom-made systems located in the company's data center and cloud computing platforms. Diversity also applies to the organization's data repositories and information handling processes, which serve as a typical object of analysis for creating a prototype solution.

The approach proposed in Section 5 was applied to accommodate the modeling of primary and secondary attributes for organizational context. Making use of pre-acquired components – set of context dimensions, services and metamodels – a further modeling session was conducted to implement the CASAD matrix modeling method, and data from project meetings were collected. The following subsections describe case-specific steps depicted in Figure 4 one by one.

6.1 Modeling Session

During the modeling session, a set of activities based on identified business needs was acquired; business needs were identified during meetings with the customer. The context dimension set was obtained by performing a literature analysis and supported modeling to group the potential context model attributes and guide the modeling session.

The activities were associated with the business needs identified in project meetings. Business needs that need to be supported through contextualization are defined in natural language. With the business needs in mind, the first set of CASAD matrix, a set of activities, was defined. These activities relate to the functionalities supported by information technology, which may be carried out with or without contextualization. See the summary in Table 5.

Having these activities in mind as the elicited customer requirements, further mappings could be made.

6.2 Mapping of Activities and Services

Based on the theoretically defined set of services (Table 4) and on practically elicited necessary activities (Table 5), an activity-services matrix was created (see Table 6). Only a subset of the services is necessary to support all activities defined from a business perspective. In the context model, services related to user activity support are mainly needed, with business-level support also slightly affected, but services related to system performance support are irrelevant. This is also consistent with the literature analysis, which demonstrates that there are no tasks related to system performance that are complementary to the tasks of knowledge management solutions and context-aware systems. Some services related to knowledge management, such as knowledge storage, are also unnecessary to perform the activities. Within the analysis, an assumption was made that the knowledge structure, in this case, would be a specific ontology or other human-readable structure.

Table 5. Set of activities

The description of business interest	Corresponding activity	Activity ID	Activity links to context model and explanation
Sorting, ordering, and e-mail forwarding of the general (main) e-mail box	Sorting based on parameter *x*	A1	Since the parameters for sorting and ordering e-mails are unclear, the sorting parameters will depend on context attributes and context-based processing.
Preparation of short document content abstracts	Support of human-computer interface (HCI)	A2	Abstracts are primarily used to display information in HCI as well as to improve the functionality and productivity of the work via HCI.
Determining the information objects belonging to concrete business processes; determining whether the formally defined business processes correspond to reality	Information flow, workflow, or knowledge flow support	A3	In general, information object relations to business processes are closely linked to the definition of flows between business processes. Analyzing these flows would also allow business-level decisions to be made.
The classification of information objects based on their content	Content classification for various purposes	A4	Content classification can be used for multiple business needs.
Context-aware search	Information object search by parameter *x*	A5	Since the parameter set for searching is unclear, the parameters will depend on context attributes and context-based processing.

Table 6. Activity-service matrix

Service	Title of the service	A1	A2	A3	A4	A5
S1.1.	Classification of current users					
S1.2.	Improving the system’s performance					
S1.3.	Adapting the system’s performance to various functioning modes					
S1.4.	Support of HCI performance					
S2.1.	Support of HCI functions		x			
S2.2.	Displaying information objects		x			
S2.3.	Classification based on criticality			x		
S2.4.	Context-aware queries for ordering	x				
S2.5.	Context-aware queries for search					x
S2.6.	Context-aware content delivery				x	
S2.7.	Identification of similar information objects				x	
S2.8.	Delivering recommendations					x
S3.1.	Deriving business rules for business process analysis			x		
S3.2.	Prediction					
S3.3.	Delivering recommendations for decision support					
S3.4.	Storing knowledge					

6.3. Existing IS Data Analysis

Context dimensions were further elaborated from the theoretically identified set to discuss and consider all the potentially relevant attributes. **User-dependent context** is a generic dimension that includes user and user habit data. The user-dependent context is explicitly defined for the user and is therefore used in systems where customization depends on various user attributes, such as habits, interests, etc. With the help of user-dependent context, the system is adapted to a specific user or uses another user as an additional data source. Examples of such systems are recommendation systems or tutoring systems, where contextualization aims to directly support the user's interaction with the system or the tasks the user performs. In addition, attributes specific to the user context can be applied for purposes other than user modeling.

In the case of knowledge management function support, the user-dependent context will include the attributes associated with the information. It can be inferred from the previously created activity-services matrix that the user and user needs will play a central role in the solution. At the same time, the user's work is mainly modeled on the specific work roles rather than individuals – so the user, in this case, might be an organizational role or a set of tasks to be performed.

Location and temporal context dimensions are usually defined separately from the user-dependent context. Although the boundaries between these context dimensions are not strictly defined, the location and temporal context are typically specified for different items and can hold different semantic meanings. For instance, a document might have a time axis that describes how it was created and modified, where it was created, etc. Each student in an e-study course can have model completion times. In document analysis and knowledge management, it is essential to follow the temporal context and attributes characterizing it.

Social situation context describes attributes associated with the structure of a group of people. Social networks, especially, include social activity-related indicators, such as liked or shared posts. Within the organization, the social situation context will consist of the users involved, groups of users, working groups, etc. These attributes show how the organization's employees interact with each other and who have similar interests based on role, project, or business process.

Activity context reflects an item's procedural context, such as what activities the item is used within. In the case of an organization, the processes can be business processes, but in the case of specific management solutions, they are modules that carry out particular functions. The activity context is similar to the system strategy-related context. Still, the system strategy-related context is associated with the system's objectives rather than activities or functions.

The item-specific context is characteristic of specific systems. In some solutions, item-specific context attributes can be classified into other types of context, such as user-dependent, temporal, or location context.

From the activity-services matrix, it can be concluded that the system strategy-related context will not be used, as it is primarily related to intelligent systems (as opposed to systems that implement intelligent functions) or the system's overall performance. Given that context is modeled for information objects, most context attributes will be associated with a specific item, that is, an information object. The location context was discarded because the location in the document system is irrelevant.

6.4 Sorting Attributes

A set of attributes was obtained from the investigation of the organization's data and the modeling session. For each attribute, it was determined whether it should be obtained directly from the system or requires a metamodel: attributes were sorted into **primary** and **secondary attributes.** A mapping between dimensions and retrieved attributes was defined. The mapping is presented in Table 7.

The coding of an attribute is used as follows:

- information object (IO) type is labeled as

- inner (IN) or
- external (EXT).

Table 7. Primary and secondary attributes

Type of attribute	The ID of an attribute	Semantic explanation	Type of context
Primary	IO timestamp	Timestamp – time received or time last modified	Temporal
Primary	IO created	Timestamp – time of creation	Temporal
Primary	IO author	The author of the information object or the sender of an e-mail	Social situation
Primary	IO rights	Information object's access rights	Social situation
Primary	IO type	The type of information object – an e-mail or a document	Item-specific
Primary	IO extension	The extension of a document	Item-specific
Primary	IO size	The size of an information object	Item-specific
Primary	IO text	Full text of an information object	Item-specific
Primary	IO title/subject	The title or subject line of an information object	Item-specific
Primary	IO attachment	In the case of an e-mail – there can be multiple attachments	Item-specific
Primary	IO domain	E-mail domain	Item-specific
Primary	IO path/IO tech address	The path of an information object	Item-specific
Primary	IO confidentiality	Confidentiality of an information object	Item-specific
Secondary	IN IO BP	Class of a business process	Activity
Secondary	IN structure	Internal hierarchy of an organization	Activity
Secondary	EXT line of business	Division	Activity
Secondary	EXT project	Project to which an information object is attached	Activity
Secondary	Forward BP	The result of the activity	Activity
Secondary	User suggestion	Suggestions related to the document	Activity
Secondary	IO author position	The role of the author of an information object in the organization	User-dependent
Secondary	IO target	The receiver of an e-mail or a group of employees with access to the folder	Social situation
Secondary	EXT partner	Partner to whom the information object is attached	Social situation
Secondary	IO class	The information object class, such as (application, complaint, minutes, etc.)	Item-specific
Secondary	IO direction	Incoming/outgoing	Item-specific
Secondary	IO urgency	Urgency	Item-specific
Secondary	IO severity	Severity	Item-specific
Secondary	IO emotional level	The intensity of the sentiment in the text	Item-specific
Secondary	IO language	Latvian, English	Item-specific
Secondary	IO sentiment	Sentiment of the text	Item-specific
Secondary	IO annotation	Annotation of information object	Item-specific

6.5 Mapping of Attributes and Services

Based on the proposed approach, it would be necessary to create a service-attribute matrix after sorting attributes. However, given that the attribute sets in this use case were defined purposefully already, the structure of this matrix is trivial – all of the attributes listed are required to retrieve Group 2 services, that is, services related to user activities (from Table 4).

6.6 Mapping Primary and Secondary Attributes

Primary attributes, such as file metadata, are acquired directly from the system. However, while the set of attributes extracted from the literature and acquired during the modeling session is theoretically possible, in practice, the availability of primary attributes may be hampered by (1) technical availability and (2) semantic meaning. Technical availability in this context means data may not be technically available for different reasons. Semantically, while technically available, the attribute's values may make little sense because of human error or the system's characteristics; therefore, further analysis for attribute refinement might be required.

Secondary attributes can be obtained either (a) by transforming primary attributes with an algorithm or metamodel or (b) by obtaining them entirely from the metamodel. So, retrieving some secondary attributes will require a set of specific primary attributes, while others will be selected from the metamodels. Table 8 shows which primary attributes are required to retrieve secondary attributes.

Table 8. Dependence of secondary attributes on primary attributes

	IN IO BP	**IN structure**	**EXT line of business**	**EXT project**	**Forward BP**	**User suggestion**	**IO author position**	**IO target**	**EXT partner**	**IO class**	**IO direction**	**IO urgency**	**IO severity**	**IO emotional level**	**IO language**	**IO sentiment**	**IO annotation**
IO timestamp																	
IO created																	
IO author		x					x										
IO rights				x					x								
IO type																	
IO extension																	
IO size																	
IO text										x		x	x	x	x	x	x
IO title/subject				x													
IO attachment																	
IO domain				x					x								
IO path																	
IO confidentiality																	

In addition, a set of metamodels is required because primary attribute values must be processed or interpreted to retrieve secondary attribute values.

6.7 Model Identification to Obtain Secondary Attributes

As mentioned above, some secondary attributes, i.e., those that do not have matching primary attributes in Table 8, are retrieved directly from metamodels. The set of potential metamodels to consider was defined a priori, as discussed in Section 5.2. Although the processing of specific metamodels and algorithms refers to the creation of a context model, not to the selection of data (hence the second stage of the project), the models that could potentially be used to obtain different attributes were defined during the modeling session and meetings (see Table 9).

To assess the possible applicability of the LLM for the acquisition of secondary attributes referred to in Table 9, a feasibility study of the LLM capabilities for the extraction of the secondary attributes of the IO has been performed. Varied types of documents (*xlsx*, *pdf*, and e-mail) have been retrieved from the organization's repositories, and their content was analyzed with two web versions of LLM: LLaMA 2 and ChatGPT 3.5. The following query was used: "*Make a contextual assessment of the following document text, answer with JSON, stating only class of a document, urgency, severity, emotional level, language, sentiment, and annotation of the document content in 50 words:*" to obtain results. LLAMA 2 had been chosen as a prospective open-access model (the most recent version at the moment of analysis), while the free version of ChatGPT has been used as one of the highest-rated commercial models for result comparison.

Table 9. Potential use of models to retrieve different secondary attributes

The ID of an attribute	Corresponding metamodel
IN IO BP	Business process model
IN structure	Model of organizational structure
EXT line of business	Metamodel of the organization's external interactions
EXT project	Metamodel of the organization's external interactions
Forward BP	Business process model
User suggestion	Model of organizational structure
IO author position	Model of organizational structure
IO target	Shared data metamodel, User groups metamodel
EXT partner	Metamodel of the organization's external interactions
IO class	IO class ontology or dictionary
IO direction	Interpretation model
IO urgency	Language processing model
IO severity	Language processing model
IO emotional level	Language processing model
IO language	Language processing model
IO sentiment	Language processing model
IO annotation	Language processing model

Looking at the specific case of a domain-specific e-mails written in Latvian, it can be concluded that both models interpret the prompt and the values to be retrieved semantically correctly (see Table 10).

Table 10. An example of the result of LLM for obtaining secondary attributes

Result of LLaMA 2:	**Result of ChatGPT 3.5:**
"class": "Business", "urgency": "Low to Medium", "severity": "Low", "emotional_level": "Neutral", "language": "English", "sentiment": "Informative", "annotation": "Itinerary for a business trip to Agritechnica 2023"	"class": "Logistics/Travel", "urgency": "Medium", "severity": "Low", "emotional_level": "Neutral", "language": "Latvian", "sentiment": "Neutral", "annotation": "The document is an itinerary for attending Agritechnica 2023 in Hannover. It includes travel details such as departure from Liepāja, accommodation in Sleem&Go Hotel Magdeburg, and plans for attending the exhibition. The tone is informative and professional."

There are slight differences in the result (e.g., urgency – the LLaMA model defines it as "Low to Medium," ChatGPT as "Medium"), a different class dictionary (the LLaMA model defines the IO class as "Business," ChatGPT as "Logistics/travel", similarly various sentiment classes are named differently). In determining the language, however, the LLaMA model is mistaken as the document contained English words but it was primarily written in Latvian.

It is inferred from this preliminary review that the use of LLM is prospective in the extraction of secondary IO attributes. In order to improve the results obtained by the models, prompt engineering must be carried out, the possible values of attributes need to be unified, and the most appropriate LLM for the task must be selected after more extensive testing on the given task.

6.8 Determining the Relevant Attributes

After retrieving the potential set of primary and secondary attributes, as identified in Tables 7 and 8, further inspection proceeds to distill the attributes and calculate the secondary attributes based on primary attributes and/or metamodels. For the illustration, here, we use the secondary context attribute "IN IO BP" as an example. This attribute denotes the organization's inner business process to which an information object belongs and is part of the activity context dimension. In the modeling session, it was concluded that the IN IO BP attribute could be inferred from the organization's business process model, as described in Table 9. In practical experiments, the applicability of LLM straightforward to IO text was also tested to retrieve one of the predefined business processes from the information object's (e-mail, document) content. These experiments assured the necessity for the application of metamodels to guide the recognition of a particular business process within an organization. Figure 5 depicts the dependency schema for calculating the secondary attribute "IN IO BP" of an IO. This process uses the content of a document (primary attribute "IO text"), data regarding access rights of an IO, denoting the organizational unit from which the IO originates (primary attribute "IO rights"), the author of an IO (primary attribute "IO author"). LLM receives both the text itself and the subset of the organization's business processes, reduced by the access scope, as a list for prompt expected outputs. Meanwhile, the author of a document might be searched within a model of organizational structure to extend or validate the prospective correspondence with the selected business process. Precise calculation is a part of the preprocessing element. This example shows that the refinement of secondary attribute retrieval might continue after the modeling sessions.

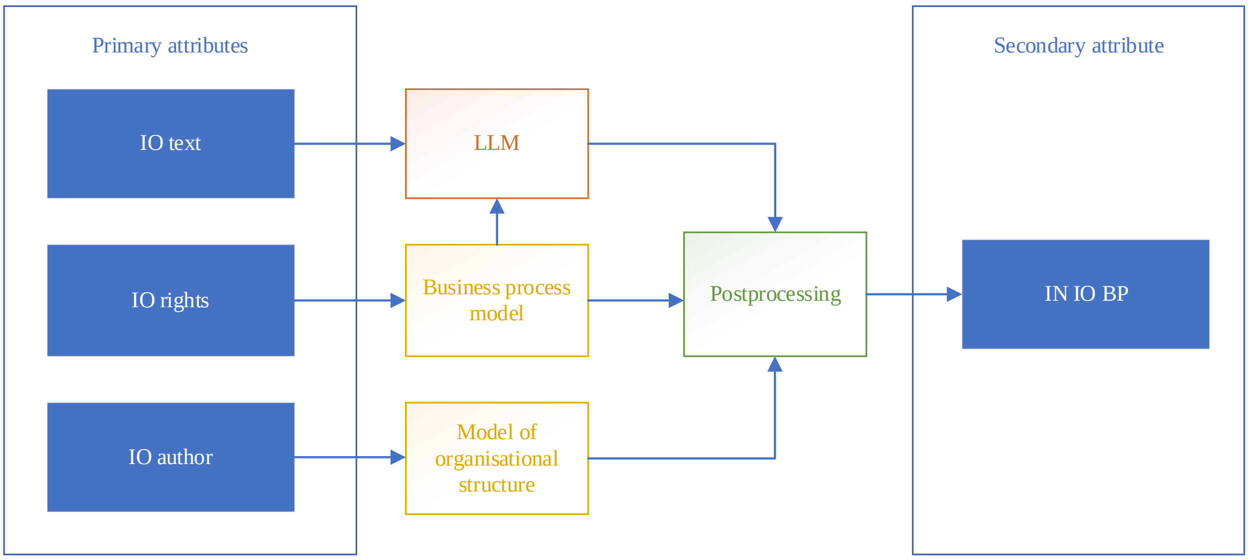

Figure 5. Deriving a secondary context attribute from primary attributes and metamodels

Similarly, retrieval of other secondary attributes shall be determined and tested. Building the context model is a proceeding process of context attribute extraction.

7 Conclusions

In this article, we explore the contextualization of information objects toward supporting knowledge management in digital workspaces. We discuss the ties between the knowledge management process and context-aware solutions, context types, and possibilities for extracting case-specific context models. An approach for extracting a set of context attributes is proposed and demonstrated in a real-case scenario. This approach extends the body of knowledge of context-aware computing and supports the development of personalized digital workspaces. The context-aware solutions for knowledge management systems differ in the aspect of where the information is obtained. It was concluded that while, in many systems, the context information can be directly obtained from the source, in the knowledge management systems, this source is often subjective – i.e., human organized work environment. For this reason, the article has extended and supplemented the modeling approach based on the CASAD modeling matrix that can be used to create context-aware knowledge management systems. The analysis has led to a defined set of activities, dimensions, and services, that can be reused, thus contributing a modeling method for context-aware knowledge management systems. The research combines context-oriented knowledge management systems with the much larger field of context-aware systems.

The next step involves deriving secondary context attributes and defining algorithms of context models supporting specific activities and workspace needs. Preliminary research suggests that in this particular case, LLMs can at least partly extract the required secondary attributes and this direction is pursued in further research.

Future work includes developing further a digital workspace solution prototype for a cloud service environment. This prototype, based on the models created from the research with elaborated details, will offer technical capabilities and functions for gathering information objects from heterogeneous data sources, document storage and processing, metadata generation and enhancement, providing a corresponding user interface for a personalized digital workspace environment.

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