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# Concept for human-machine interfaces for resilient data extraction from digital twins

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With the rising digitalisation of the construction industry, digital twins evolve as a tool for data management. The accumulation of data in a digital twin over the lifecycle of an infrastructure building yields extremely large datasets. This creates the need for an intuitive interface to extract data from the digital twin. The fast, reliable, and user-friendly extraction of specific information from this data source will be key for safe and resilient operation of infrastructure in the future. Chat bots leveraging deep learning techniques for natural language processing (NLP) have evolved quickly as human-machine interfaces (HMI). This work picks up the idea of using NLP in an HMI and investigates the data processing that is necessary to enable data extraction from a digital twin. The concept is based on a natural language inquiry, which is preprocessed to extract the intentions of the information request. With the intentions, the context for a question answering (QA) task is chosen, which will be used to extract the answer from the digital twin by a deep learning model. Furthermore, this work will discuss the challenges and opportunities which the described concept would face upon implementation.
*Keywords*: Digital Twin, Construction, HMI, ChatBot, Deep Learning, Knowledge Management, AI, Project Management, Data Structure.

## 1. Introduction

As various studies prove, the digital twin in the architecture, engineering, and construction (AEC) industry gets more and more attention. With the emerge of building information modelling (BIM) already, a highly visual representation is provided which can be used to link, store and access further information. (Errandonea et al. 2020; Hosamo et al. 2022; Shahzad et al. 2022; Pregnolato et al. 2022) As the density of information in the digital twin increases, it could become increasingly difficult for users to find the information they need. This could result in information overload. (Edmunds und Morris 2000) So new ways to engage our information systems, like the digital twin, are needed. These must be easy and intuitive to use while providing accurate and resilient information from the digital twin. In this paper, we will first discuss the state of the art in knowledge management for projects to motivate our approach. Next, we will present the current technological advancements in the field of ChatBots and there use as Human Machine Interface (HMI). This will be followed by the introduction of our own concept for a data processing structure designed to realize a HMI for construction projects. Subsequently, we will delve into a comprehensive discussion on the merits and potential pitfalls of our proposed concept. The paper will conclude with a summary of our findings, and a look towards future research prospects and developments in this domain.

## 2. Literature Review and State-of-the-Art

This section picks up the definition of digital twins in the AEC sector, presents approaches to knowledge management in projects and explains the methods proposed by the authors. It also presents the state of the art in human-computer interfaces (also called HMI) and their use in project knowledge management.

### 2.1 The digital twin in construction and asset management

The BIM model is the first step towards a digital twin in the AEC sector. It yields a highly graphic and intuitive approach to technical information. But the digital model is not capable of handling all the information accumulated over the lifecycle of an object. For example, the model can not handle real-time data from sensors in the operations phase or from changing external conditions. The idea of BIM is based on manually updating a digital model. With the bidirectional connection of the physical object and the virtual object, a system emerges that always represents the latest state of the physical object and is even capable of predicting future states based on its active state. This is a common definition for the digital twin in the AEC sector. (Boje et al. 2020; Sacks et al. 2020)

## 2.2 Knowledge management in Projects and approach suggested by the authors

There are different approaches to knowledge management in projects. In Table 1 (a morphological box), three different approaches are presented. Knowledge Database, Document Management System (DMS), and Expert Based Knowledge Management. Although digital knowledge management tools are common in modern projects, often the preferred way to get information in projects is still to ask a project member (often a co-worker). The reason for this is that you can speak your natural language and get expert information directly from a team member without having to think about the right search terms, the location of your information in a database or a DMS. However, the source of the information needs another workforce to provide the information to you. In the worst-case scenario, this worker will have to send you some information in digital or physical form, so that the question generates a lot of human work. A database, which generally stores all types of information in one place and is accessible in the project, seems to be the best solution to this problem. To ensure that the information is up to date, an automated update process would be the best solution. In the end, the user wants both a specific piece of information and the source material. The approach suggested by the authors provides the benefits of a direct question to an expert with the benefits of digital knowledge management. An optimal process would combine the positive perception of human interaction with the effectiveness of an automated updated database, while delivering the actual information and its source.

Table 1. Morphological box for different knowledge management approaches. The underlined methods are picked for the technique suggested in this Paper.

| Method | Interface | Source of Information | update process | Information delivery |
|---|---|---|---|---|
| Knowledge Database | search engine | **database** | **Auto-mated** | **latest piece of information** |
| DMS | manual Search | Data-structure | Semi manual | **source file** |
| Expert based knowledge manage-ment | **human interaction** | co-worker | manual | piece of Information |

## 2.3 ChatBots for human-computer interaction

Chatbots, in general, are a type of HMI. The idea of natural human-computer interaction goes back to experiments such as that proposed by Aalen Turing in 1950, where the idea was that a computer should communicate with a group of people without them realising that they were not communicating with a human (TURING 1950). Since then, chatbots have continued to evolve and are now a widely used tool in a wide range of businesses, such as customer service, health, industrial use cases, or education (Adamopoulou und Moussiades 2020; Okonkwo und Ade-Ibijola 2021). A general Chatbot design is whitely described in literature, for example, in (Adamopoulou und Moussiades 2020). The main components are the User Interface, the User Message Analysis, the Respond Generation Component which delivers a response to the User, and a Dialogue Management Component. The latter is directly connected to the Backend which can be a Data Base or an Information System.

While the first ChatBots used Pattern Matching to extract the content from the user input, modern systems using Natural Language Processing (NLP) (Khurana et al. 2023). Common ChatBots try to generate an answer by guessing the best next word which matches the input and the previous output (generative-based) (Adamopoulou und Moussiades 2020). That leads to the problem that the output can be wrong and is not connected to a source of the information. However, it is part of the latest research to connect the output to the source of information to verify a correct output (Deb et al. 2023).

The use of NLP is not an unknown approach to all aspects of complex projects such as construction projects. In the literature, it is for example suggested to address Legal and Contractual Matters (Hassan et al. 2021). In the following sections, we suggest the adaption of an NLP-based concept for knowledge management in complex construction or infrastructure projects.

## 3. Conception

The proposed concept pursues the idea that it is possible to communicate with the digital twin as if it were an employee of the organisation. A HMI is used for this, with which a user can communicate via chat in natural language. This interface uses various methods of artificial intelligence to generate an answer for the user request based on two connected databases.

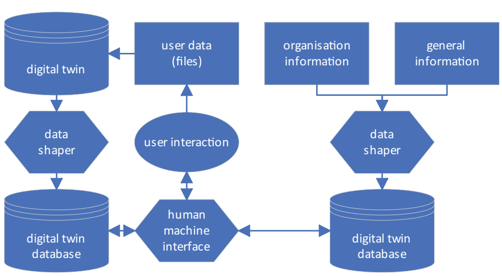


Fig. 1. System architecture for the human machine interface supported interaction with the digital twin

Fig. 1 shows the possible architecture behind the HMI. The two databases, the digital twin database and the general database, have a uniform structure and contain pieces of knowledge that are generated from different sources. A knowledge elements can be sections of text, images, graphics, model data, tables, or other information created in the life cycle. This information is described by its metadata. The metadata columns are used as features by the HMI neural networks. The difference between the databases is that they are fed from different sources. The general database contains units of knowledge from internal and external data. Information from internal data can come from organisational charts, from the process database, from product data, from internal guidelines, from older projects, or from other organisation-specific sources. The external pieces of knowledge are generated from external information relevant to the general project management of the organisation. The data can come from legislation, recognised rules of technology, standards, or similar framework, and generally applicable documents.

The second database, the digital twin database, is an image of the data collected in the digital twin that has been optimised for machine learning. In the digital twin, all the data generated during the life cycle of an asset is collected. (Pregnolato et al. 2022) This includes data generated by sensors, for example, as well as data stored and linked in the form of files by involved users. The digital twin database contains the pieces of knowledge that can be extracted from the data generated, stored, and linked over the life cycle. This can be, for example, classic data such as documents, model data (IFC), data linked to the model (BCF), tables, audio/video data from recordings of video calls or emails. The databases are separate, since the digital twin database is asset-specific and built up over the lifecycle, and the general database, although it has to be kept up to date, can be used for each asset.

Data, whether from the digital twin or from internal or external sources, are prepared in the same way using a data shaper for the respective database. All data are classified using a neural network to determine what type of file it is. (Khan et al. 2010) According to their classification, the pieces of knowledge are extracted from the data by another neural network. For example, a PDF file would be broken down into individual paragraphs of text, individual figures, and individual tables. (Shen et al. 2021) At this point, the original source file and its storage location must not be lost. Therefore these are stored in a metadata vector. To ensure the best possible performance of the HMI, as much metadata as possible should be saved. In addition to the source file and storage location, important metadata would include author, role of the author, creation date, specific type of information, and a content vector. The content vector is also generated by a neural network and consists of a uniform number of keywords that describe the knowledge elements. (Nasar et al. 2019) In addition to the metadata vector, an adjacency matrix can also be generated from the digital twin. This maps the links between the individual pieces of information in the digital twin.

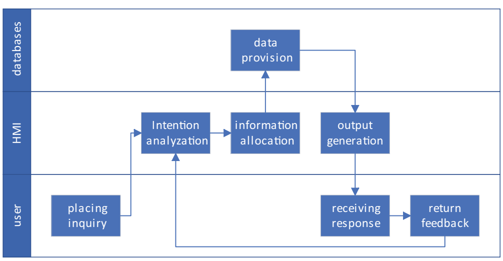


Fig. 2. Processing of the user inquiry via the human machine interface to receive response from the databases

Fig. 2 shows the process of human interaction with the digital twin via the HMI. The inquiry placed by the user is processed in the HMI. The HMI must take two logical steps to gather the information. First, the intention of the request has to be determined and second, the requested information has to be allocated in the databases. This question answering (QA) task could be done in different ways. An option described by Dasigi et al. is the use of a semantic parser. The parser uses bidirectional Long Short-Term Memory neural networks. The output is a request for tabular data in a logical form. With this database request, the information requested by the user can be extracted from the databases. (Dasigi et al. 2019) Another approach by Herzig et al. uses a transformer-based network, which combines both steps. Therefore the placed inquiry is extended by the table which contains the requested information. Inquiry and table are separated by a separator token. This combination is used as input for the transformer, which will then directly return the cell coordinates of the most likely answer to the request. (Herzig et al. 2020) Both approaches seem to be able to perform the intention analyzation and further allocate the information in the databases. With the data that are provided by the databases, an output needs to be generated. The output should consist of a direct answer in natural language and a link to the source of the information, so that the user has the option to recheck the information. The source is the link to the actual file containing the piece of information. The path to that file is stored in the meta-data of the information piece. The textual response to the inquiry is generated based on the information given. This is probably handled best by another transformer-based language model. (Li et al. 2021)

## 4. Discussion of concept

The proposed concept would face challenges upon implementation, but also comes with opportunities for information management in construction projects, for example, digital twin data. Regarding the challenges, probably the learning phase of the model would be the most crucial to name. Although the basic system can be trained on existing internal and external data, the project-specific model can be developed only throughout multiple projects. The, per definition, different course of each project require a larger data pool to increase the generalization capabilities of the model. (Khanna und Mollá 2021; Jain et al. 2020) Studies that train BERT models on smaller datasets show difficulties in making predictions. While these results are based on unusual languages, the effect could probably be counteracted by keeping the information in English. (Jain et al. 2020) Further, these challenges could be mitigated by synthetic project data and requests, as the use of synthetic data in other fields shows. (Bartolo et al. 2022; Puri et al. 2020) These data could be generated by an existing knowledge management system or by evaluating email communication from existing projects, which focusses on information exchange between participants. There are also minor challenges and risks associated with the described concept. The easy approach to accessing the digital twin data could result in overdependence of the users. Additionally, users could become overdependent on the system and may face a decrease of their critical thinking capacity. Since the returned information from the digital twin is actually created by other participants in the project, the interaction with the digital twin could suggest over-reliability.

However, the implementation of the described concept could significantly improve information retrieval. This is shown by similar projects in different but comparable sectors. In the medical sector, for example, information extraction from databases also needs to be resilient, and the typical database search requests bind medical personal. The QA implementation reduces the retrieval time from several minutes to as little as 6 seconds. (Lee et al. 2006) Further, the aspects of a single source of truth (SSoT) match the intentions of the concept. With the digital twin as SSoT and an HMI as the only interface for information extraction, the quality of the requested data can be improved. (Pang und Szafron 2014)

## 5. Conclusion and Outlook

As shown, leveraging artificial intelligence for information extraction from a digital twin can be an efficient and user-friendly approach that combines the amenities of human-like interaction with the potential of centralised information and knowledge management. In this scenario, AI models that perform well on QA tasks, such as BERT, outperform text generation models due to increased resilience of the output. Furthermore, the SSoT aspect can improve the quality of the requested information.

However, further research is still necessary. The biggest challenge to overcome is the generation and preparation of the data. First, the actual extraction from existing project data or the deployment of information and knowledge management systems that are designed to gather data for machine learning. Also, the preprocessing of the large unstructured data, which represents the digital twin in the first place. In this way, the different data sources can be combined to an actual, structured digital twin database.

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