Towards a client-based digital twin for decision making: a workforce integration use case

Ghina Kassem[1], Stella Gatziu Grivas[1] and Arianna Fedeli[2]

[1]University of Applied Sciences and Arts Northwestern Switzerland, Olten, Switzerland
[2]Gran Sasso Science Institute, L'Aquila, Italy

Abstract

The integration of individuals with diverse backgrounds and support needs (e.g., refugees or immigrants) into the labor market remains a persistent challenge, driven by skill shortages, high employee turnover, and organizational difficulties in managing diversity, standardization, and knowledge continuity. In response to these challenges and the growing complexity of public workforce integration, this research explores how Digital Twin (DT) concepts and AI-powered chatbots can support human-centered decision-making processes. This paper introduces a Client-Based DT concept, enhanced by a Large Language Model (LLM)-supported chatbot. By combining internal client data with external integration program attributes, the system generates personalized roadmaps and provides real-time support without replacing expert guidance. Using a Design Science Research approach, a prototype was developed through iterative modeling and chatbot testing via Retrieval-Augmented Generation (RAG). Applied in the Swiss public sector, the prototype enhances continuity of knowledge and collaboration between experts and clients. Despite challenges in data integration and legal compliance, the findings show the potential of Client-Based DTs in improving public service delivery.

Keywords

workforce integration, chatbots, client-based digital twin, digital twin, digital transformation, public sector innovation, human-machine collaboration

1. Introduction

The current workforce integration landscape is characterized by a pressing shortage of skilled professionals, particularly in the fields of social work and workforce integration. Mikhaylov et al. [1] explain how this shortage is further intensified by high employee churn rates, which not only disrupt the continuity of services but also compromise the effective management of knowledge and expertise. The loss of experienced professionals can result in a significant loss of unspoken knowledge, making it challenging for organizations to maintain the quality and consistency of their services. Recent global developments, such as the ongoing digital transformation and increasing generational diversity and demographic changes [2], have added complexity to employee engagement within the public sector [3, 4]. Within this context, the main problem lies in the ineffective integration of migrants, refugees, and social benefit recipients into the Swiss primary or secondary job market. This is due to complexities like language barriers, education, and recognition of foreign qualifications, combined by organizations' struggles with diverse client attributes, external factors, and a lack of standardized processes, tools, and knowledge management. Consequently, integration efforts suffer from inefficiencies, inconsistent outcomes, and a lack of personalized support, making economic growth and social inclusion even more difficult than it currently is [5, 6]. In this paper the term *client* reflects the terminology within the Swiss integration landscape (e.g., refugees, asylum seekers, and where explicitly noted other social-benefit recipients), however our artifact can be generalized to user/citizen in other public sector settings.

Developing a tool for workforce integration can enhance the capabilities of professionals, such as case workers and job coaches, who play a critical role in the integration process. The human element remains a critical component of the workforce integration process, and the system should be designed

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ghina.kassem@students.fhnw.ch (G. Kassem); stella.gatziugrivas@fhnw.ch (S. G. Grivas); arianna.fedeli@gssi.it (A. Fedeli)
0009-0003-4986-4002 (G. Kassem); 0000-0003-4376-1697 (A. Fedeli)

to complement, rather than replace, the expert interactions that are vital for building client trust, which is essential for successful integration outcomes. As the landscape of work transforms and skilled labor shortages intensify, the search for smarter, more adaptive approaches to workforce integration is at the forefront of societal innovation.

In the contemporary digital landscape, the concept of a DT has emerged as a transformative technology, offering a virtual representation of a physical entity, system, or process [7]. The significance of DTs has made an immense impact, as they serve as a bridge between the physical and digital entities, enabling real-time data analysis, simulation, and control to optimize performance and facilitate decision-making. The application of DTs extends across various sectors, including manufacturing, healthcare and urban planning where they are used to create more personalized, efficient, and sustainable solutions. This paper positions itself within the broader field of digital transformation research by exploring how DTs can support strategy development and implementation based on the use case of workforce integration and new business models in the public sector. In particular, it highlights the relevance of DTs to the field of social work and workforce integration, where they offer new pathways for modernizing the current coaching and integration processes, enhancing service delivery, and informing data-driven based decisions in human-centered contexts [8].

Digital transformation represents a fundamental rethinking of how organizations function, driven by the integration of digital technologies into all aspects of work, service delivery, and strategy [9]. In the public sector, this transformation disrupts established routines and demands a reassessment of daily workflows and collaborative practices. The digital transformation also drives the urgent need to develop digital skills and capabilities among staff to adapt to new digital tools and methods [10]. Emerging technologies such as artificial intelligence and chatbots play a central role in this evolution. AI is increasingly recognized for its ability to transform public service delivery, offering applications in risk prediction, early intervention, and personalized citizen engagement [1]. Chatbots, as part of the generative AI ecosystem, further support digital transformation through real-time interaction, decision making assistance, and service automation [11]. However, integrating these technologies into public organizations requires overcoming resistance to change, breaking down silos, and building collaborative, cross-sector ecosystems [1]. Effective digital transformation focuses not only on technology but on organizational change that fosters partnerships and uses shared resources for public value creation. Wimmer and von Bredow [12] explain how the public sector is undergoing a digital transformation, with governments using new technologies to improve efficiency, transparency, and service delivery. Governments are increasingly using big data analytics for data-driven decision-making to understand public needs [13, 14]. However, their application to workforce integration, particularly within public administration and e-government services, remains underexplored.

In this paper, we propose the development of a Client-Based Digital Twin (Client-based DT) approach that can improve this issue by providing a digital repository of client information and integration pathways, which directly facilitate knowledge retention and transfer [15]. While governments increasingly use data analytics for service optimization [1], a more personalized and interactive use of DTs could help design tailored integration paths and better respond to individual client needs.

Although the Client-Based DT does not enable a continuous real-time loop, it supports an eventual synchronization pattern that is sufficient for contexts where immediate feedback is not critical. This enables meaningful analysis and adaptation based on periodically updated states. A more interactive and client-specific implementation of DTs could enable the design of tailored integration pathways, offering dynamic guidance that adapts to individual profiles and evolving circumstances. In this regard, we propose the integration of the Client-Based DT with conversational technologies such as chatbots that, as an interface between users and the DT, can provide personalized feedback, support decision-making, and help simulate different integration scenarios in a more accessible way [11]. Switzerland presents a compelling testcase for developing and evaluating a Client-Based DT in public service delivery due to its federalized structure, multilingual population, and cantonal variations in integration policy implementation. The Integration Agenda Switzerland (IAS) provides a standardized national framework while leaving room for local adaptation, resulting in diverse program taxonomies, legal interpretations, and resource allocations. These conditions mirror the complexity, fragmentation, and need for personalization that other countries face in workforce integration efforts.

To reach this aim, we plan to answer the following research questions:

(RQ1)*: Which elements are necessary to design and develop a Client-Based DT model?*

(RQ2)*: How can a tool built on a model of a Client-Based DT predict integration challenges for different client groups? What are the key components and functionalities?*

To answer these questions, we discuss an approach to designing a Client-Based DT, supported by a conversational chatbot, to simulate, guide, and optimize individual integration journeys. Artificial intelligence techniques are applied to client-specific attributes (e.g., skills, needs, barriers) to generate dynamic and personalized roadmaps for workforce inclusion. We follow Design Science Research principles [16] and apply iterative methods to develop and refine the Client-Based DT model.

2. Adressing the need for a client-based DT

When the DT concept was introduced in 2003, digital representations of physical products were still in their infancy and not widely developed. The DT concept has evolved to become a critical component in understanding the relationship between a physical product and its digital counterpart, facilitating a closed-loop product lifecycle that can reduce costs and foster innovation [7]. In line with traditional difficulties to create generic DTs, the Client-Based DT, which involves several specifications and considerations that ensure that the digital representation accurately reflects the physical entity and its environment. A key obstacle to realizing Client-Based DTs lies in achieving data standardization and effective management of the substantial data generated, which is intensified by unresolved data ownership challenges requiring clear legal frameworks, as noted by Jones et al. [17]. Javid et al. [18] establish that effective DTs necessitate integrated digital systems with communication, interoperability, and strong data management supported by bidirectional physical-virtual links. Building on this, Javaid et al. [20] argue that the fundamental step of defining appropriate fidelity, often achieved through detailed high-fidelity modeling, allows for precise simulations crucial for expert insights and design enhancements. Several works are currently exploring the development of digital representations of clients. Van der Aalst et al. [19] propose that using hybrid intelligence, combining human and AI, is key for building more robust and resilient DTs capable of improved decision-making and innovation, highlighting the need for a clear distinction between static and dynamic attributes for the creation of DTs, specifically Client-Based DT. Lin et al. [20] propose the creation of Human DTs, where attributes such as human external data, human psychological data, human behavioral data, human-human social interaction data, and human environment data are an essential prerequisite. They envision several representation layers, one for the physical world (client attributes and engagement data), one for the digital world (data processing, integration with external information, and modeling), and a "Human-Computer Interface" layer for expert-client interaction and collaborative roadmap building. However, this approach lacks an integrated conversational interface and decision-support tools to actively guide clients along personalized integration pathways.

In addition, frameworks play a key role in the successful creation and implementation of Client- Based DTs by providing a structured approach to their development and deployment, supporting the definition of key components, relationships, and processes involved in building and managing these complex digital representations. Nikula et al. [21] highlight how one critical function of these frameworks should be facilitating the integration of data from diverse sources. This includes integrating data from sensors, wearable technologies, and other sources to create a comprehensive and accurate representation of the individual. According to Basu, Corradini and Fedeli et al. [22, 23, 24, 25], the development of DT solution, especially a Client-Based DT, could necessitate a well-defined bridge connecting the physical entity with its digital representation. [26] further mentions how frameworks should also provide guidelines for data privacy, security, and responsible data usage, ensuring that the rights and privacy of individuals are protected. This is particularly important considering the sensitive nature of the data involved in creating Client-Based DTs, which may include personal health information, behavioral patterns and preferences, and other sensitive metrics.

However, **at the current stage**, there is a lack of frameworks or structured approaches that fully support the design, development, and deployment of Client-Based DTs. This gap becomes increasingly critical as personalization, user-centric design, and adaptive decision-making become central pillars in domains such as healthcare, education, and digital services.

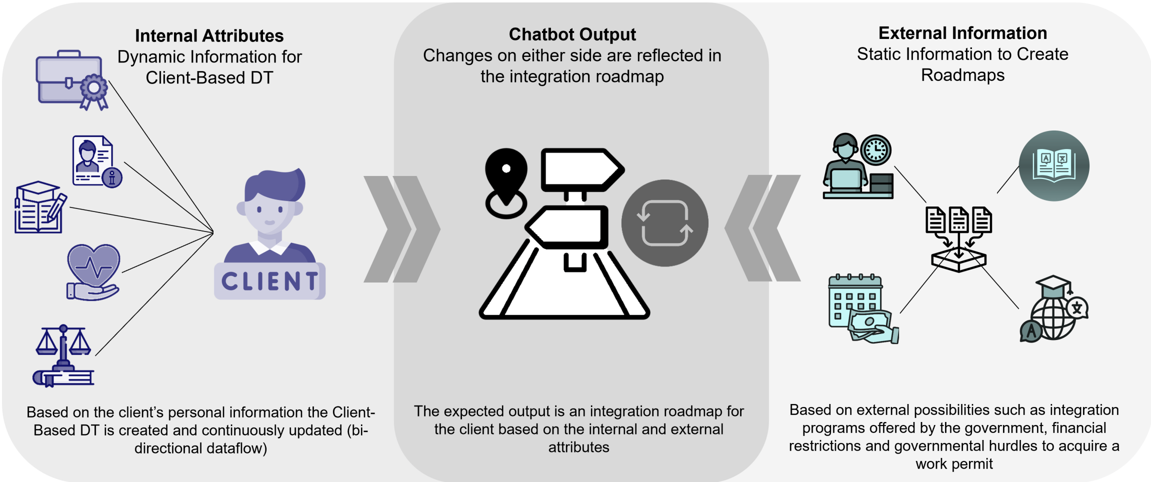
In comparison to a DT, a decision support system (DSS) aggregates data to recommend actions, but typically does not maintain a continuously updated, versioned state of a specific individual nor support bidirectional synchronization with operational sources. The client-based DT states has a person-level simulation which would include what-if scenarios on the same evolving twin. The human-in-the-loop governance includes explicit checkpoints where coaches/clients accept, modify, or reject actions and decisions which would report back to the twin. A Client-Based DT is not merely a technical innovation but a paradigm shift: it allows for the individualization of services, enabling real-time (or near real-time) insights, simulations, and adaptive guidance tailored to the specific needs, behaviors, and contexts of each user. In contrast to centralized models, a client-side DT supports autonomy, local decision-making, privacy-preserving analytics, and resilient operation in environments with limited connectivity or strong regulatory constraints. Moreover, emerging challenges such as the need for explainability in AI, the growing demand for ethically aligned personalization, and the importance of hybrid human-AI collaboration all point toward the necessity of modeling the individual client as a digital entity that can interact dynamically and meaningfully with complex systems. Therefore, we argue that the development of Client-Based DTs represents a strategic priority for the evolution of DT research, demanding dedicated methodologies, architectures, and tools capable of supporting context-aware, interactive, and ethically grounded digital representations of individuals.

3. The use case of Swiss workforce integration

To better understand the need for a Client-based DT, we propose the Swiss Workforce Integration as a use case. Switzerland, with its multicultural society, strong education system, and flexible labor market, provides a distinctive context for workforce integration. As highlighted by Buchmann [27], demographic shifts will significantly affect Switzerland's labor force by 2030, with fewer young workers and more aged 55 and older. Zurich, an economic center, is especially equipped to tackle integration challenges arising from demographic changes, globalization, and technological advancements. Krebs et al. [28] emphasize workforce integration as essential beyond economic necessity, recognizing employment as a vital aspect for individuals' self-worth, societal value, and financial independence. Effective integration involves inclusive, collaborative approaches engaging professionals from diverse fields like healthcare, social work, and governmental services, offering client support toward sustainable employment. Geissen and Widmer [29] identify complexities within the integration process, specifically with refugees, underscoring cultural hurdles, language proficiency, education, and policy variations across Swiss cantons and municipalities as significant factors influencing integration outcomes. Budliger [30] further asserts that integrating migrants, refugees, and social benefits recipients is vital economically and socially. Effective strategies require understanding local labor demands, cultural workplace norms, and providing early interventions such as language and vocational training, skill recognition, and continuous support [31]. Coaches facilitate skill refinement through interactive methods, helping clients navigate workplace expectations and overcome barriers despite ethical considerations remaining central throughout this integration process [32].

The Swiss workforce integration landscape involves many interconnected aspects, primarily led by cantonal and communal authorities who navigate a complex set of processes fitted to diverse clients, ranging from Swiss nationals, migrants, expats, and refugees. These public employment services assess individual capabilities, offer coaching and job placement, and often collaborate with entities such as language schools and social and workforce integration programs, increasingly utilizing digital tools, including the national job portal www.job-room.ch. While the State Secretariat for Economic Affairs provides primary guidance, regional employment assistance offices, and communal integration coaches are key players, working alongside employers and training institutions to encourage a supportive

Figure 1: High-Level Process of the Client-Based DT



ecosystem. Social welfare, guided by the Swiss Conference for Social Welfare, complements this by ensuring basic needs are met while prioritizing economic and personal independence through workforce integration, acting as a safety net. The Integration Agenda for Switzerland further streamlines the process for refugees and asylum-seeking individuals through initial orientation and systematic potential assessments, leading to differentiated integration pathways.

Despite these efforts, the landscape faces difficulties stemming from varied resource allocation and implementation across cantons and municipalities, communication challenges between internal and external stakeholders, and the complexities encountered by individuals with diverse backgrounds, all impacting the effectiveness and consistency of support services and sustainable integration efforts.

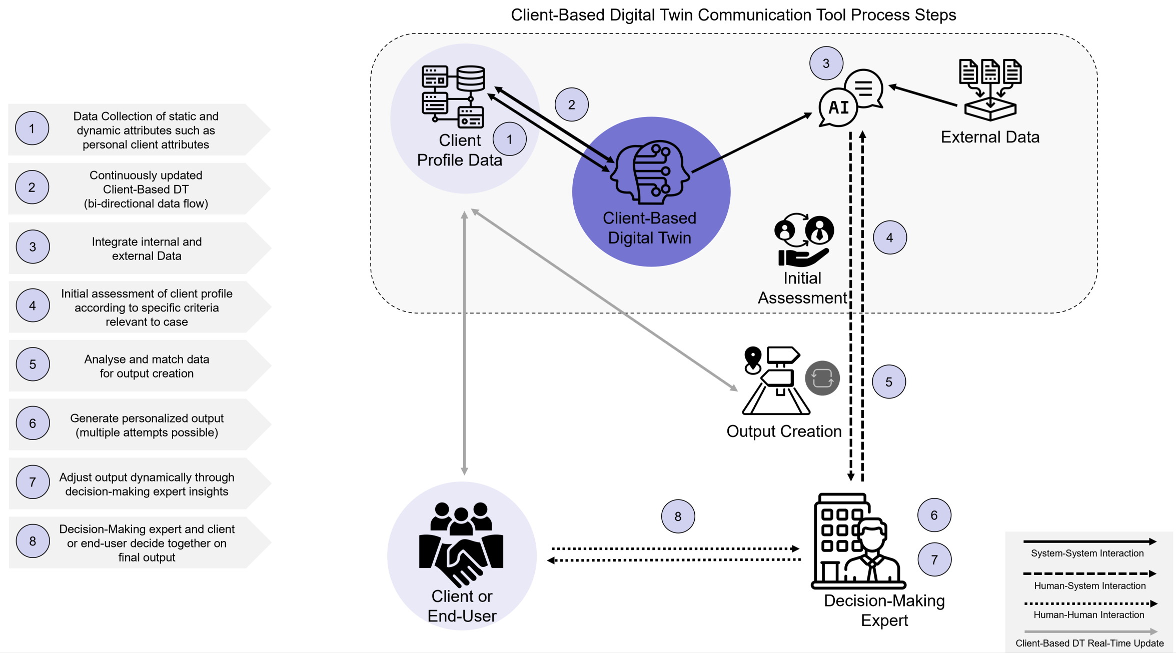
4. The client-based digital twin approach

Following the Design Science Research principles outlined by Kuechler et al. [16], these insights will be applied to the iterative research process to systematically develop and refine the Client-Based DT approach, comprising models, attributes, and components. In the *Awareness* phase, theoretical foundations on DTs were explored to identify practical challenges and user needs. In the *Suggestion* phase, insights from the literature were integrated to define the Client-Based DT, with special attention to modeling human-centric and dynamic attributes. A preliminary *Development* phase involved creating a working prototype, using realistic client personas using a Switzerland workforce integration case study. Future DSR iterations will lead to a complete evaluation of Client-based DT.

The concept of the Client-Based DT demonstrates wide-ranging applicability across multiple scenarios that focus on individual client personas. In contrast to traditional DT models, which are generally oriented toward physical objects, processes, or entire organizations, the Client-Based DT is specifically developed to capture the dynamic attributes that stem from the client's persona, skills, specific biological data, and individual restrictions. This human-centered approach supports its implementation in a variety of contexts where personalized guidance and informed decision-making are required.

We propose the application of the Client-Based DT with an external chatbot to create a dynamic digital environment where client information and external factors are integrated to support experts (such as coaches) in individual decision-making and guidance, as illustrated in Figure 1. The Client-Based DT continuously updates to reflect the most current state of the client, while the chatbot serves as an intelligent agent, allowing experts to interact naturally with the tool. The adaptive nature of this tool guarantees that any change, whether in the client's situation or the external environment, is immediately reflected in the DT, maintaining the relevance and accuracy of the information presented to both users and professionals.

Figure 2: Process of the Client-Based DT development and usage.



4.1. Client-based digital twin development and usage

Several steps are necessary to develop a Client-Based DT. Figure 2 illustrates the process for generating and managing workforce integration roadmaps using a Client-Based DT communication tool. The process begins with the collection of the client's personal information according to specific attributes (Step (1)).

This includes structured data (e.g., demographics, employment history) and unstructured data (e.g., interview transcripts, behavioral logs). Data sources span both internal (e.g., previously collected agency records) and external systems (e.g., public authority databases, healthcare, or education systems). Data ingestion pipelines are designed to ensure consistent formatting, semantic alignment, and compliance with privacy regulations (e.g., GDPR).

The Client-Based DT is then continuously updated using event-driven architectures or periodic synchronization mechanisms, ensuring the digital profile remains in sync with the client's evolving situation (Step (2)). A bidirectional data flow is maintained through API integrations and secure data brokers, allowing both system-driven updates (e.g., policy changes) and user-driven inputs (e.g., self-assessment updates). Version control and state history mechanisms ensure traceability and rollback capabilities during the lifecycle of the DT.

In Step (3), the Client-Based DT is dynamically integrated with external workforce integration data. This includes semantic data matching to access and align opportunities, programs, legal frameworks, or regulatory constraints from governmental or organizational sources. We envision that possible data modeling with ontologies and knowledge graphs supports the alignment of heterogeneous datasets, ensuring consistency and interoperability.

Then, an initial client assessment by an expert is conducted, combining both personal and external information to gain a comprehensive understanding of the client's integration needs and available opportunities (Step (4)). This phase is supported by an interactive interface and decision-support dashboard, which aggregates and visualizes multi-source data from the DT. Experts use this dashboard to perform a guided qualitative assessment, enriched by system-generated suggestions derived from rule-based logic and predefined evaluation criteria (e.g., eligibility thresholds, regional policy constraints). Natural language processing (NLP) modules may also be employed to extract relevant information from unstructured expert notes or client-provided documents, ensuring no critical input is overlooked. In Step (5), the DT analyzes the consolidated dataset to generate a personalized integration roadmap.

The Client-Based DT employs artificial intelligence through a Retrieval-Augmented Generation (RAG) engine to process and synthesize this information, thereby supporting roadmap creation. A personalized integration roadmap is generated and presented to both the client and the Integration Coach for review and action (Step (6)).

As the client and coach interact over time (Step (7)), the roadmap can be dynamically adjusted in real time, reflecting ongoing feedback, observable progress, and any changes in the client's situation or the external context. Finally, the outcomes and updates from the integration process are fed back into the Client-Based DT (Step (8)), ensuring that it remains an up-to-date, central reference point for all stakeholders involved. The legend of Figure 2 provides further explanations for the communication dynamics between human and system entities. Solid arrows indicate system-to-system exchanges, capturing automated data flows and communications between components such as the Client-Based DT, external data stores, and the chatbot. Dashed arrows represent system-human interactions, through which the chatbot or DT delivers RAG-enhanced insights, assessments, and draft roadmaps to the decision-making expert. Dotted arrows illustrate human–human collaboration, reflecting direct dialogue, either face-to-face or virtual, between the Integration expert and the client as they interpret, refine, and enact the proposed steps.

It is important to note that, although the chatbot generates and updates recommendations, it does not possess the authority to finalize any course of action. Every suggestion remains advisory. The Integration Coach and the Client jointly review and validate the chatbot's output, making explicit decisions on the next integration steps (Step (8)) and dynamically adjusting priorities (Step (7)) through collaborative engagement. In this structure, the chatbot functions strictly as a strategic consultant and data synthesizer, while all ultimate decisions are made by the human users, namely, the Integration Coach and the Client.

4.2. Client-based digital twin attributes

As discussed before, attributes are the main core for the Client-Based DT and the external chatbot tool. The client attributes are essential for creating a live digital representation of each individual and are organized into two sub-categories, consisting of *client information* and *client restrictions*.

Figure 3: Attributes used for building the Client-Based DT and the External Chatbot

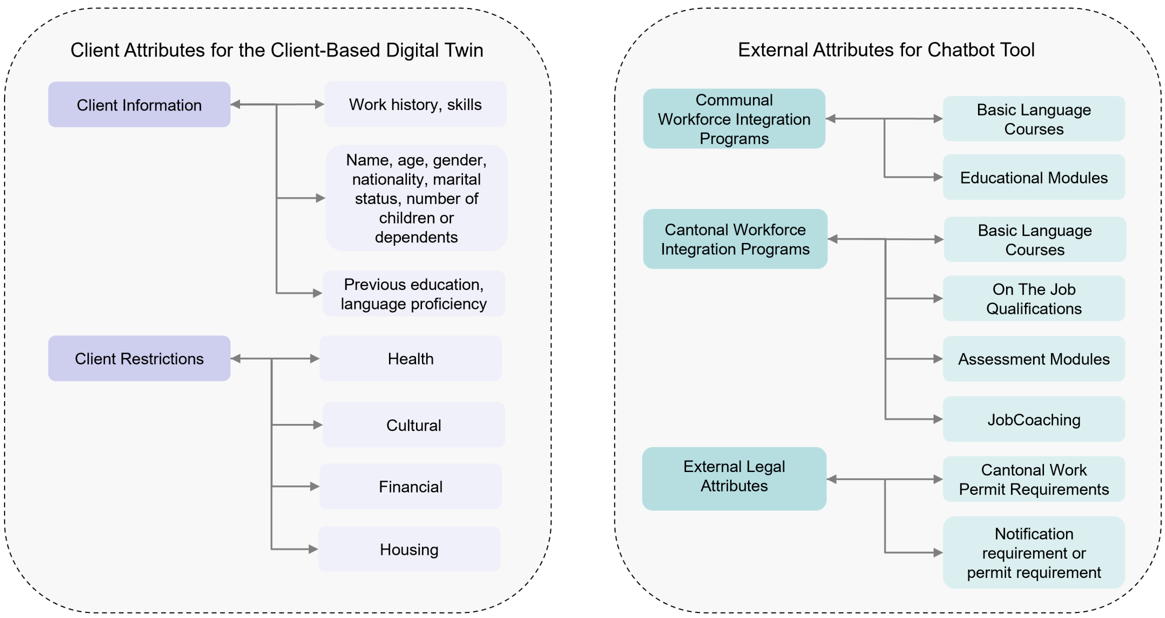


Figure 3 explains the structured approach needed to build a Client-Based DT based on the use case of workforce integration. These attributes include demographic and personal background data, the client's work history, skills, age, gender, nationality, marital status, number of children or dependents, previous education, and language proficiency. Client restrictions identify possible barriers, including possible health issues, and cultural, financial, and housing aspects. These client attributes are mostly dynamic and must be continuously updated as the client's situation evolves, distinguishing the Client-Based DT from static digital models or digital shadows. In contrast, the external attributes serve as input for the external chatbot tool, which is designed to communicate with the Client-Based DT and support the generation of integration roadmaps. These external attributes, such as communal and statal integration programs, basic language courses, educational modules, job coaching, and legal requirements, are generally static and do not require frequent updates.

While the attributes are presented in a static form, we are currently developing an ontological data model to represent them as a Knowledge Graph. This structured, semantic representation will allow for advanced reasoning, eligibility inference, and intelligent query answering. Through the use of OWL classes and SPARQL queries, the system can dynamically match client profiles to suitable programs and services based on their current attributes and constraints. For example, Listing 1 proposes using SPARQL-based inference rules within the system to identify clients with an A1 language proficiency who are not enrolled in any course and dynamically suggest relevant language programs. The following rule formalizes this logic by constructing a recommendation link between the client and suitable courses within the knowledge graph.

Listing 1: SPARQL rule to suggest A1-level language courses to clients

```
CONSTRUCT {
  ?client :shouldBeSuggested ?course .
}
WHERE {
  ?client a :Client ;
        :hasLanguageProficiency "A1"^^xsd:string ;
        :isEnrolledInCourse false .

  ?course a :LanguageCourse ;
        :courseLevel "A1"^^xsd:string .
}
```

4.3. The domain-specific chatbot

Developing an effective chatbot as an intelligent interface for interacting with the Client-Based DT requires the integration of multiple engineering components and the selection of attributes that constitute both the core of the Client-Based DT and the external information layer. The selection process must prioritize attributes that are already available or can be reliably accessed within the organization's existing data infrastructure.

The continuous synchronization mechanisms are required to collect both static and dynamic client data, ensuring that any updates in the client's profile are instantly reflected within the DT. This requires both capturing the data and coordinating ongoing data exchanges between multiple data sources and the DT platform.

To merge operational data from both the DT tool and the client database, a layer for processing language and data interoperability is necessary, facilitating the integration of diverse datasets and tools. This layer includes a data translation module that maps heterogeneous input formats (e.g., JSON, XML, RDF) into a unified schema, based on the underlying ontology of the DT. Semantic alignment and entity resolution mechanisms are employed to ensure data consistency and accurate mapping. Once data is processed and verified, the tool must provide a user-friendly output interface, presenting insights through a DT representation that informs users about the client's progress and potential areas for improvement. This can be achieved using a multi-modal UI framework that combines textual feedback, visual progress indicators, and interactive elements derived from the LLM output.

The chatbot operates as a hybrid pipeline, combining static prompt templates with dynamic context retrieved from the DT knowledge graph. It must be able to reason over structured client profiles, infer constraints, and personalize recommendations accordingly. This requires a modular backend architecture including a prompt generation module, a data retrieval engine, and a logic-based recommendation layer. The chatbot's effectiveness relies on the design of structured prompts that guide its interaction process. These prompts should be sequenced logically, beginning with questions about the feasibility of workforce integration and progressing to more detailed queries concerning specific constraints, preferences, and anticipated outcomes.

We envision a system in which prompt chaining is used to guide the dialogue, where the output of a previous step serves as structured input to the next. This allows the chatbot to adapt the conversation flow based on evolving client data, progressively narrowing down integration options. Subsequent prompts facilitate the generation of multiple integration roadmaps, encouraging the exploration of alternative strategies based on varying combinations of client attributes and organizational possibilities.

5. Testing and evaluation

A first prototype of a RAG-based chatbot was developed that combines information retrieval with text generation capabilities. Rather than using a basic Large Language Model (LLM) alone, our chatbot employs an external knowledge base that retrieves relevant documents in response to user queries, significantly improving the accuracy and completeness of responses.

As a technological service, we rely on the Amazon framework. Amazon S3 serves as the storage solution for original user documents, which supplement the inherent knowledge of the LLM. Amazon Bedrock offers a variety of pre-trained AI models for embedding and completion of tasks, and it can integrate with other AI providers like Cohere. Pinecone is utilized as a managed vector database optimized for quick similarity searches and efficient retrieval in high-dimensional spaces, making it well-suited for AI-driven search recommendations and NLP applications.

To evaluate the chatbot's capacity for personalized workforce integration planning, a case study was conducted using a representative client persona drawn from the internally developed dataset. This persona, inspired by real-world client profiles encountered by integration organizations, includes detailed demographic, educational, linguistic, and personal attributes that may influence the feasibility and structure of an individual integration roadmap. Table 1 presents the complete client profile used in the case study. The individual is a 36-year-old woman from Syria with refugee status, residing in Switzerland for nine years. She has limited formal education, basic language proficiency in German, and no formal work experience. In addition to these constraints, she faces several personal and structural limitations, including child and household responsibilities, cultural boundaries regarding acceptable workplaces, limited commuting flexibility, and health restrictions that prevent physically demanding labor.

Based on this profile, the chatbot was prompted to generate a tailored workforce integration roadmap that aligns with the client's constraints, competencies, and potential. The prompt design aimed to replicate the step-by-step logic of a professional coaching session, gradually narrowing down feasible options based on specific contextual limitations (e.g., childcare availability, commuting time, minimum income thresholds). Initially, prompts assessed a client's general integration possibility. Subsequently, these prompts were refined to explore solutions under specific limitations, such as budget, time, or family constraints. The overarching goal was to produce structured, step-by-step roadmaps for workforce integration, personalized to individual client needs and considering legal and financial factors.

In parallel, the external workforce integrated data has been conducted as a group of fourteen integration organizations were selected to test the tool. For each organization, a PDF file was created, detailing a range of available programs including integration, language, and vocational training opportunities. These offerings were categorized according to various criteria such as cost, age, experience level, language requirements, and geographic proximity to the client, and were also presented in tabular form. Pre-requisites for the chatbot's effectiveness include the continuous adjustment of these internal and

Table 1
Client Profile use case

Date of birth	20/03/1987
Gender	feminine
First nationality	Syria
Second nationality	none
Third nationality	none
Marital status	married
Number of children above 18	none
Number of children under 18	3
Dependent family members	yes, husband who is sick and mostly home, all the household work is on her, mostly responsible for child well-being
Permit	B-FL
Refugee status	B, recognized refugee
Years living in Switzerland	9 years
Drivers License	none
Previous education (highest level of education)	none, basic primary school in Syria, 6th year finished
Language proficiency in formal German	A1
Language proficiency in Swiss German	none
Other language proficiency	Arabic (B1)
Other language proficiency	Kurdish (C1)
Other language proficiency	none
Proven work history in Switzerland	none
Proven work history abroad	none
First work history	none
Second work history	none
Third work history	none
Soft skills	basic communication skills, patient due to circumstances at home
Hard skills	no IT skills available, started driving lessons
Health restrictions	can not carry more than 15kg due to a previous pregnancy complication
Cultural restrictions	will not work at any restaurant or bar in a serving position, must be home during the early mornings and evenings due to child care responsibilities
Financial restrictions	must earn more than CHF'500.00 monthly to cover all personal expenses
Housing restrictions	can commute up to 0.5 hours from the main station by public transport
Previous integration process	has not completed any German courses
Previous integration costs total	CHF -
Previous integration costs (German)	CHF -
Previous integration costs (Assessment & Coaching)	CHF -
Previous integration costs (IAZH)	CHF -

Table 2
Example of an Integration Program derived from the Chatbot

Organization / Offer	Description	Logistics	Target Group	Costs
Academia Integration ICT educational module	Basic knowledge of computer applications is required to access the job market. Vocational training is difficult without ICT skills. Participants gain sound ICT knowledge and MS Office skills tailored to vocational and workplace needs. The education module includes 5 modules at 3 levels (school years 4, 8, and 11). Can be combined with Fit for the Job Market and/or Mathematics modules. *IAZH Accreditation: yes*	Location: Zuerichstrasse 131, 8600 Duebendorf Also offered at: Gruezefeldstrasse 34, 8400 Winterthur 4 lessons/week for 22 weeks (duration may vary). Courses are offered continuously throughout the year. Without childcare. Entrance: Continuous enrollment is possible.	Adolescents/ Young adults (16-25), Adults	ICT Basics: 2,376 CHF ICT Structure: 2,376 CHF ICT Advanced: 2,376 CHF Materials: 80 CHF

external attributes based on chatbot output and design sprint analysis, with the potential for further detailed explanations of attribute data to enhance the specificity of the generated workforce integration roadmaps.

To ensure a realistic evaluation of the chatbot's capabilities, ten questions were formulated. These questions aimed to assess the chatbot's ability to conduct an initial analysis of the client personas, to summarize the profile data accurately, and to generate tailored integration roadmaps. Some questions specifically directed the chatbot to consider financial or legal constraints when designing the integration roadmaps. Upon uploading all internal and external information into the chatbot interface, initial testing revealed challenges in processing the tabular data format. To resolve this issue, all relevant information was rewritten as structured, flowing text and re-uploaded. Once reformatted, the chatbot successfully responded to all questions, providing comprehensive summaries for each client persona and generating individualized workforce integration roadmaps that aligned with the unique needs and restrictions of each profile.

The output produced by the chatbot is shown in Table 2, which presents an integration program that was automatically retrieved and recommended by the system. The selected program emphasizes basic ICT training, a critical skill set identified as a prerequisite for both vocational training and employment access. The recommendation includes details on course content, duration, locations, and associated costs, while also indicating that the program is suited to adult learners and does not require childcare. Importantly, the roadmap also reflects logistical feasibility with respect to the client's geographic mobility and financial situation.

After the chatbot generates the initial integration roadmap and analysis, the client and integration coach review the output together to discuss its relevance and feasibility, considering the client's current situation. The chatbot's response serves solely as a discussion foundation, offering structured insights and individualized recommendations based on the data provided. However, it does not make any decisions or determine the final course of action. If the client and coach identify new priorities, constraints, or opportunities during their discussion, they may prompt the chatbot again with additional specifications to receive an updated and refined roadmap. Once a mutual decision is reached, the chosen integration plan is implemented in real life and reflected in the Client-Based DT, ensuring that the evolving status and actions are accurately reflected in the digital representation.

This case study illustrates how the RAG-based chatbot can support human-centered decision-making by generating personalized and data-driven integration pathways. It further demonstrates the potential for digital systems to enhance the initial stages of counseling by providing structured, explainable, and adaptive recommendations that respect complex personal constraints. All test data and the results of the answers to the chatbot are accessible here[1].

5.1. Discussion and insights

The evaluation of the Client-Based Digital Twin prototype was informed by feedback (during 5 interviews) from both integration coaches and clients, revealing a generally positive reception alongside critical areas for refinement. Integration coaches reported increased confidence in the AI's ability to support vocational integration, particularly praising the speed, analytical depth, and structured format of the generated roadmaps. These features were seen as useful for streamlining routine tasks, enhancing professional decision-making, and adding contextual value to client consultations. However, concerns were raised about information overload due to the text-heavy output, which could overwhelm both coaches and clients, especially non-native speakers. To improve usability, coaches recommended offering alternative formats, such as visual maps, and enriching the outputs with metadata like estimated time, cost, and success likelihood. There was also a divergence in opinion about how outputs should be shared: while one coach cautioned against directly presenting unfiltered roadmaps to clients, another viewed them as effective brainstorming tools, contingent on accuracy and reduced hallucinations. The coaches emphasized that real-world effectiveness should be measured using KPIs such as job placements, course completions, and roadmap revision frequency, supported by clear rollout guidelines.

Clients echoed this dual sentiment of enthusiasm and caution. They appreciated the clarity and structure of the AI-generated roadmaps and believed the tool could save valuable time during consultations, allowing for more focused in-person interactions. While experienced AI users highlighted the benefit of clearly defined options, others with less technological familiarity warned that complex prompts could cause frustration. Several clients recommended visual enhancements to cater to diverse learning preferences and called for the inclusion of key planning details such as timeframes and costs. Trust in AI appeared to be growing, yet clients insisted that human judgment should guide final decisions. A critical concern was the use and protection of personal data. At least one client expressed discomfort in

[1]https://github.com/AriannaFedeli/Client-based-DT

sharing sensitive information without the ability to limit access or request data deletion post-integration. Despite these reservations, most clients welcomed the idea of using the tool as a discussion aid and expressed interest in exploring the roadmap independently, provided sufficient IT support and data safeguards were in place.

Insights from the evaluation reveal several practical enhancements that can improve the current process steps of AI-supported workforce integration tools. Feedback from integration coaches highlighted the need for automated access to up-to-date external resources, leading to the integration of direct weblinks to official workforce databases and policy portals. This change reduces manual data maintenance and ensures that generated recommendations reflect the latest program offerings and regulatory conditions. Additionally, both coaches and clients found the text-heavy outputs difficult to interpret, particularly for individuals with limited digital or language proficiency. In response, the process was enhanced by embedding estimated durations, cost breakdowns, and visual flowcharts into each recommended step, helping users better understand the implications and feasibility of each option. Another critical improvement was the expansion of client-facing interfaces, enabling read-only access to integration roadmaps while maintaining safeguards around information sharing and verification. These enhancements promote shared decision-making, improve transparency, and tailor the tool to the needs of diverse users, ultimately making the system more inclusive, efficient, and actionable in real-world vocational contexts.

6. Limitations

Existing DT architectures, such as the Human DT and Customer DT, differ significantly in process steps and underlying assumptions when compared to a Client-Based DT approach. The Human DT focuses heavily on modeling cognitive and biological processes such as perception, attention, and decision-making which is primarily used for medical or behavioral applications, relying on physiological and environmental data inputs to simulate human functioning [33]. In contrast, the Customer DT process centers around psychological profiling, using personality models to predict consumer behavior and personalize marketing strategies. Both models prioritize individual-level data but are optimized for narrow, domain-specific outputs such as medical insights or marketing effectiveness [34]. Neither DT variation incorporates dynamic interaction loops or external structural constraints such as legal or programmatic eligibility. These limitations highlight a fundamental difference in how the processes are structured. While existing DTs are generally designed to support understanding or affect decisions, the Client-Based DT takes an iterative approach to data processing, working alongside human agents and social systems to produce individualized pathways that respond to real-world constraints and the evolving needs of the individual clients [35].

However, integrating the Client-Based DT into existing public service infrastructures presents additional limitations. The continuous collection and synchronization of personal data (both static and dynamic) requires consensus on data formats and update intervals, without which outdated client profiles may compromise recommendation accuracy. Moreover, widely used case management platforms do not currently expose the secure portal interfaces required for DT integration, and aligning legacy data schemas with the DT's ontology demands significant development resources and cross-team coordination. Staff adoption poses another challenge, as varying levels of digital literacy may lead to errors or hesitancy in using the chatbot interface, necessitating structured training and support.

7. Conclusion and future work

This paper introduced a Client-Based DT and chatbot prototype aimed at supporting workforce integration. The prototype demonstrated the potential of combining structured personal data with contextual knowledge to generate personalized integration roadmaps and inform professional decision-making.

Prototype testing revealed difficulties that will be addressed in data handling, especially the chatbot's initial inability to process tabular formats, which was mitigated by converting data into continuous text. Further issues include the lack of standardized data formats and the need to ensure compliance with legal and privacy regulations such as the GDPR. The handling of sensitive information, such as health, financial, or legal status, requires strict safeguards, particularly when scaling the system to new domains or regions. While this work focused on public sector applications, the Client-Based DT approach holds promise in other contexts. In healthcare, for example, patient-specific DTs could support treatment planning, while in education, they could inform personalized learning. Commercial use cases, such as personalized marketing or customer behavior simulation, could also benefit from individualized digital representations.

In future development and deployment of the Client-Based DT, ethical considerations must be integral to the design, especially given the system's reliance on sensitive personal data and algorithmic decision-support. The AI4People framework [36] provides a useful foundation with its five guiding principles, beneficence, non-maleficence, autonomy, justice, and explicability, which are particularly relevant for systems interacting closely with vulnerable individuals. Autonomy, for instance, requires that clients and professionals maintain control over the decision-making process and retain the ability to override AI-generated suggestions. Moreover, since DTs often collect more granular personal data than traditional systems, ensuring transparency and preventing misuse or profiling becomes critical [37]. These concerns are echoed in broader debates around AI governance under GDPR and the EU AI Act. Empirical studies also show that public acceptance of AI varies with perceived fairness, discretion, and risk, particularly in the public sector, where human judgment is preferred in high-stakes decisions [38, 39, 40]. As such, ensuring explainability and accountability of AI outputs such as required by the explicability principle is vital to building trust and ensuring ethical alignment with human values [37].

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT for Grammar and spelling check. After using these tools/services, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

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