Towards a Taxonomy for Digital Assistant Technologies: Addressing the Jingle-Jangle Fallacies

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This study proposes a unified taxonomy for Digital Assistant Technologies (DATs) to resolve terminological inconsistencies and eliminate »Jingle-Jangle fallacies.« By employing a systematic taxonomy development method on 137 papers, the framework categorizes DATs across four meta-characteristics: AI technology, context, intelligence, and interaction. This taxonomy facilitates the clear differentiation of three primary DAT concepts: assistant, chatbot, and agent. By providing a structured framework, the study enhances conceptual clarity, fosters more focused research, and ensures better alignment of DATs.

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1 Introduction

Recent advancements in Artificial Intelligence (AI), particularly of Generative AI (GAI), have intensified competition among organizations leveraging these innovations for productivity, efficiency, and strategic advantage (Khaokaew et al., 2022; Oldemeyer et al., 2024). Digital Assistant Technologies (DATs), including chatbots, intelligent personal assistants, and intelligent agents (Bowman et al., 2024; de Barcelos Silva et al., 2020; Nenni et al., 2024), drive digital transformation through customer service, task automation, and personalized support. A challenge in DAT research is terminology inconsistency, where terms are used interchangeably or identical terms describe distinct functionalities, creating a jingle-jangle fallacy (Block, 1995; Henry & Liu, 2024; Marsh et al., 2019). Studies show that various terms like Conversational Agents (CA), Virtual Agent (VAG), and Conversational AI Agents (CAIA) often describe overlapping functions (Ahmad et al., 2022; Grimes et al., 2021; Gupta & Dandapat, 2023), complicating research consolidation and technology classification. Broad labels like digital assistants further blur distinctions by unifying diverse DAT, such as voice assistants, AI chatbots, and chatbot assistants, under an overly generalized term (Gkinko & Elbanna, 2023; Sharma et al., 2024). This inconsistency complicates efforts to consolidate research, making it harder to build on existing knowledge and clearly identify the defining features and capabilities of these technologies. Our previous systematic literature review (SLR) of 137 academic articles (January 2013-May 2024) identified 39 distinct DAT terms across three categories: assistants, chatbots, and agents (Preiß & Westner, 2025). Among these 137 papers, only two taxonomy papers were found (Hanelt et al., 2015; Schmidt-Kraepelin et al., 2018), both narrowly focused on specific DAT applications. This reveals a significant gap in standardized classification, leading to our research questions (RQ):

- RQ1: What dimensions and characteristics are essential for constructing a rigorous and generally applicable taxonomy for DATs?
- RQ2: How can a rigorous and generally applicable DAT taxonomy enhance conceptual clarity and practical usability?

This paper addresses these questions by proposing a unified taxonomy that systematically organizes DATs based on shared characteristics. Using Nickerson et al.'s (2013) taxonomy development methodology, refined by Kundisch et al. (2022), we aim to reduce terminological ambiguity and enhance classification coherence. Our study contributes to Information Systems (IS) research by providing a robust framework for categorizing emerging DATs (Nickerson et al., 2013; Schmidt-Kraepelin et al., 2018), advancing digital transformation literature understanding in this domain.

2 Background and related works

2.1 Research background

DATs drive digital transformation by automating interactions, enhancing customer engagement, and reshaping organizational processes (Bălan, 2023; Choudhary et al., 2024; Pais et al., 2015). From Eliza's scripted responses in 1966 (Weizenbaum, 1966), to today's natural language processing (NLP)- and machine learning (ML)-powered chatbots, they have evolved from rule-based systems to context-aware, adaptive assistants supporting diverse tasks, including customer service and legal guidance (Choudhary et al., 2024; Y. Li et al., 2023). This shift positions DATs as enablers of human-machine collaboration (Shneiderman, 2020), moving beyond command-driven tools to proactive, context-sensitive partners.

2.2 Related DAT research

In recent years, an extensive number of terms describing DAT have emerged (Preiß & Westner, 2025). Terms like Virtual Assistant (VAS), Intelligent Virtual Assistant (IVA), Voice Assistant (VA), Digital Assistant (DA), Intelligent Personal Assistant (IPA), Chatbot, AI Chatbot, CA, VAG, Intelligent Agent (IA) have been employed with considerable overlap, often without consistent distinctions. For instance, Beer et al. (2015, p. 2) observed that the label 'agent' is widely used, yet there is no agreed-upon definition" and assistant and agent are frequently synonymous (Lee et al., 2024). Terms like IVA and IPA are often associated with specialized functionalities, indicating capabilities such as personalized, voice-driven interactions and adaptive responses (Alimamy & Kuhail, 2023; Pais et al., 2015; Priya et al., 2023). However, as pointed out by Ammari et al. (2019), VA has become the »industry standard« term for speech-driven assistants, despite the existence of more specific terms like IVA and IPA. These terms are applied to tools like Siri, Alexa, and Cortana, highlighting the terminological overlap (Brachten et al., 2020; C. Li et al., 2023; Porra et al., 2020;

Ripa et al., 2023). VA and IVA presents varied interpretations: some sources consider VAS an umbrella term for voice-enabled systems, while others suggest that »intelligent virtual assistant« denotes systems with more advanced, context-aware capabilities with text-based input (C. Li et al., 2023; Richards & Bransky, 2014). Chatbot and IVA exemplify distinctions between task-specific chatbots (Chen et al., 2023; Koivunen et al., 2022) and broader-function technologies like Siri and Alexa (McKillop et al., 2021; Rapp et al., 2021). Similarly, while DAs are sometimes viewed as equivalent to CAs, CAs are occasionally considered simpler, rule-based systems (Khaokaew et al., 2022; Schuetzler et al., 2020). These overlapping terms frequently lead to different concepts being conflated under similar labels. While Chatbot and CA are often used interchangeably (McKillop et al., 2021; Schuetzler et al., 2020), CA typically suggests a broader range of conversational functionality (Ngai et al., 2021), with CAs being more adaptable across applications and chatbots serving narrower, task-focused roles (Grimes et al., 2021; Schuetzler et al., 2020). A central differentiator among these assistants is the level of anthropomorphism and autonomy. Terms like IVA and IPA frequently emphasize adaptive, user-centered feature (Alimamy & Kuhail, 2023; Pais et al., 2015), while simpler VAs and CAs typically operate within rule-based, pre-programmed parameters (Behera et al., 2024; Chen et al., 2023; Stieglitz et al., 2022). Labels like »intelligent« or »personal« denote a stronger emphasis on customization. The term's application to sophisticated systems like ChatGPT (Ding et al., 2024), demonstrates the persisting jingle-jangle fallacy within the latest generation of DAT encompassing GAI. These findings underscore the need for a coherent taxonomy, as inconsistent terminology creates ambiguity evident in technologies like Alexa and Siri, described by over 11 different terms (Preiß & Westner, 2025). To our knowledge, no taxonomy fully captures DAT concepts, dimensions and characteristics, highlighting the need for a structured framework to enhance clarity in research and practice.

3 Research method: Taxonomy development process

Phenomenon and motivation (I): Taxonomies organize and classify knowledge through hierarchical relationships (Šmite et al., 2014). We build on the iterative taxonomy design process outlined by Nickerson et al. (2013) and refined by Kundisch et al. (2022), ensuring rigor and relevance in our systematic framework. This section delineates the taxonomy development process, a fundamental methodological approach in IS research that structures complex domains into organized categories (Šmite et al., 2014). According to Nickerson et al. (2013), a taxonomy is a formal system for classifying objects based on a set of characteristics or dimensions. Szopinski et al. (2019) emphasize that taxonomies must remain iterative to capture evolving IS domains effectively. The framework by Kundisch et al. (2022) integrates empirical and conceptual iterations through multiple cycles with defined termination conditions, ensuring completeness, clarity, and practical applicability. According to Nickerson, taxonomy development begins with identifying meta-characteristics, which establish the taxonomy's primary focus and direct the selection of essential dimensions. Kundisch et al. (2022) outline three preparatory steps: specifying the observed phenomenon, identifying target user group(s), and articulating intended purpose(s). The observed phenomenon is the rapid proliferation of DATs. The primary user group includes academics, researchers, and practitioners who seek a robust and systematic classification framework. The main objective and motivation is to standardize DAT terminology for clarity, consistency, and practical use. This taxonomy aims to integrate all three concepts identified in Preiß & Westner (2025), moving beyond prior taxonomy efforts that have typically focused on a single concept or isolated subsets of DATs within the scope of DAT research (Bahja & Lowry, 2021; Gkinko & Elbanna, 2023; Janssen et al., 2020; Nißen et al., 2022; Schmidt-Kraepelin et al., 2018). Meta-characteristics, introduced by Nickerson et al. (2013) define central categories and guide dimension selection. Alternative terms include perspectives (Janssen et al., 2020) or meta-dimensions (Möller et al., 2022; Rosian et al., 2021). We adopt the three-tier hierarchical structure from Nickerson et al. (2013) meta-characteristics, dimensions, and characteristics, using a multilevel index for precise organization (Saldana, 2021).

Objectives and ending conditions (II): The taxonomy development process requires (1) ending conditions (Nickerson et al., 2013) and (2) evaluation goals (Kundisch et al., 2022) before initiation. Ending conditions define when to conclude iterations based on conceptual (e.g., theoretical justification) and empirical (e.g., saturation) criteria. This study adopts Nickerson's conditions with an added meta-characteristics criterion (Szopinski et al., 2019). The evaluation goals selected for this study are 'analyzing' and 'clustering'. The analyzing goal is »investigating objects that represent a particular phenomenon, utilizing characteristics and dimensions to identify similarities and differences« (Kundisch et al., 2022, p. 432). The clustering goal focuses on grouping objects based on »identified commonalities, enabling the classification of types [...])« (Kundisch et al., 2022, p. 432). After three iterations analyzing 106 papers (most present 5 DATs from each concept; from 137 identified in Preiß & Westner, 2025), all ending conditions were met, confirming the taxonomy's robustness (Nickerson et al., 2013). The second iteration introduced three dimensions, improving clarity. The final taxonomy classified 13 DATs, representing 33% of identified DATs but covering 77% of the analyzed literature.

Development approach – conceptual-to-empirical (III): Building on the steps outlined in the previous chapters, Nickerson et al. (2013) differentiate between two fundamental approaches to taxonomy development: conceptual-to-empirical and empirical-to-conceptual. In the conceptual-to-empirical approach, taxonomy development begins with theoretical constructs or literature, which are then validated through empirical data. Conversely, the empirical-to-conceptual approach starts with data collection (e.g., case studies or interviews) to derive characteristics, which are subsequently refined and grounded in theory. This iterative nature is supported by Hevner et al. (2004, p. 88), who describe »design as a search process« that enables continuous testing and validation cycles throughout taxonomy development. In our study, we applied the conceptual-to-empirical approach, building our taxonomy on existing DAT literature in IS as discussed in the SLR (Preiß & Westner, 2025).

4 Taxonomy for DATs

4.1 Taxonomy overview

This section provides a detailed description of the meta-characteristics (MC), dimensions (D), and characteristics (C) of the taxonomy, along with the final DAT taxonomy (see Figure 1). According to Nickerson et al. (2013), a taxonomy's characteristics must be mutually exclusive within each dimension, a principle upheld during the taxonomy's development. Non-self-explanatory characteristics were thoroughly described to ensure clarity and understanding. Dimensions were systematically ordered using three criteria: alphabetical order, prevalence (low to high or less to many), and evaluation of presence (present to absent) and individual characteristics were further organized alphabetically to ensure clarity.

<table>
<tr><th>Meta-Characteristic (MCn)</th><th>Dimension (Dnm)</th><th colspan="9">Characteristics (Cnmk)</th></tr>
<tr><td>AI technology</td><td>AI models</td><td colspan="3">traditional AI models</td><td colspan="3">GAI / DL models</td><td colspan="3">none</td></tr>
<tr><td rowspan="5">context</td><td>application domain</td><td>academia</td><td>daily life</td><td>e-commerce</td><td>e-learning / education</td><td>healthcare</td><td>industry</td><td>service industry</td><td>usability</td><td>work / business</td></tr>
<tr><td>beneficiary audience</td><td colspan="3">corporate / organization</td><td colspan="3">individual</td><td colspan="3">both</td></tr>
<tr><td>motivation / goal</td><td>customer service</td><td>daily life assistance</td><td>healthcare service</td><td colspan="2">socializing / caretakership</td><td colspan="2">productivity / efficiency</td><td colspan="2">other</td></tr>
<tr><td>scenario coverage</td><td colspan="4">use case = 1</td><td colspan="5">use case > 1</td></tr>
<tr><td>service intent</td><td colspan="3">commercial Intention</td><td colspan="3">individual support</td><td colspan="3">both</td></tr>
<tr><td rowspan="4">intelligence</td><td>context awareness</td><td colspan="4">low</td><td colspan="5">extensive</td></tr>
<tr><td>degree of anthropomorphism</td><td colspan="4">low</td><td colspan="5">high</td></tr>
<tr><td>environmental adaptability</td><td colspan="4">static</td><td colspan="5">adaptive</td></tr>
<tr><td>learning ability</td><td colspan="3">pre-defined knowledge</td><td colspan="3">rudimentary</td><td colspan="3">extensive</td></tr>
<tr><td rowspan="5">interaction</td><td>appearance</td><td colspan="3">no appearance</td><td colspan="3">low appearance</td><td colspan="3">high appearance</td></tr>
<tr><td>initiative</td><td colspan="3">delegated</td><td colspan="3">mixed</td><td colspan="3">autonomous</td></tr>
<tr><td>input</td><td colspan="2">multiple</td><td colspan="2">text</td><td colspan="2">visual / gesture</td><td colspan="3">voice / speech</td></tr>
<tr><td>number of users addressed</td><td colspan="4">user = 1</td><td colspan="5">users >1</td></tr>
<tr><td>user interface</td><td>app</td><td colspan="2">device</td><td colspan="2">multiple</td><td colspan="2">proprietary software</td><td colspan="2">website</td></tr>
<tr><td colspan="2"></td><td>Order coding:</td><td>alphabetical</td><td colspan="2">less/low to many/high</td><td colspan="3">present (alphabetical) to absent</td><td colspan="2"></td></tr>
</table>

Figure 1: Thorough DAT taxonomy

Source: Own

AI technology (MC_1) includes the dimension AI models (D_{11}), which categorizes the types of AI models that power DAT. Traditional AI models (C_{111}) are rule-based systems, relying mostly on traditional machine learning techniques that perform fixed tasks by following patterns in historical data. These models are simpler, interpretable, and suited to structured, stable tasks. Examples include decision trees, Bayesian method, reinforcement learning and rule-based systems (Assaf et al., 2020; Groshev et al., 2021; Somers et al., 2019). GAI / DL models (C_{112}) use deep learning, especially transformer models, to generate dynamic responses (Okey et al., 2023; Vaswani et al., 2017). Unlike classical AI, they create new content by predicting sequences based on large datasets, allowing for flexible, context-aware interactions ideal for complex tasks like conversational AI (Rillig & Kasirzadeh, 2024). Some DATs may operate without AI, relying instead on simple, predefined logic and data sets to facilitate only basic interactions and are categorized as none (C_{113}) (Beldad et al., 2016). **Context** (MC_2) defines the environmental and situational framework in which DATs operate, encompassing implicit and explicit information about the intended user group, purpose, and domain (Abowd et al., 1999; K. Kim et al., 2018). This meta- characteristics clarifies where and why DATs operate, illustrating how they are designed or applied to fulfill specific user needs and achieve operational goals across diverse scenarios (Diederich et al., 2020; Gnewuch et al., 2017). MD_2 structures five key dimensions that encompass 22 characteristics (C211-C253). Application domain (D21) specifies the primary application area for which the DAT is designed for. This dimension highlights the variety of contexts in which DATs operates in (Zumstein & Hundertmark, 2017). Ranging from academc (C221) to work/business (C226) Beneficiary audience (D_{22}) identifies the primary user group the DAT is intended to serve. This includes corporates or organizations (C221) for professional use, individual users (C222) in personal settings, or both (C_{223}), catering to a combination of personal and organizational needs (Gkinko & Elbanna, 2021). Motivation/goal (D23) identifies the primary purpose or objective behind the deployment of DATs, clarifying what the DAT is intended to achieve for its user within a specific domain (Bittner et al., 2019). This dimension captures the role the DAT plays in supporting users' objectives in various contexts (Knote et al., 2018; Ryan & Deci, 2000). It includes customer service (C_{231}), handling customer interactions and needs, daily life assistance (C_{232}), aimed at supporting routine personal tasks; healthcare service (C_{233}), designed to address health-related needs, socializing/caretakership (C_{234}), providing interpersonal support or companionship, productivity/efficiency (C_{235}), enhancing operational effectiveness and increasing productivity, and other (C_{236}), encompassing objectives outside the described characteristics.Scenario coverage (D24) describes the DAT's design across different usage scenarios, indicating whether it is tailored for single-use case scenarios (C241) or broader applications with multiple use cases (C242). This dimension highlights the DAT's flexibility and adaptability across various contexts, showcasing its capacity to support diverse interaction needs and operational demands (Følstad et al., 2019). Service intent (D_{25}) differentiates between the primary purpose of the DAT. It includes commercial intention (C_{251}), where the DAT is designed to generate revenue directly or indirectly through its assistance, individual support (C_{252}), where the primary goal is to provide non-commercial help to users, and both (C_{253}), where the DAT combines commercial objectives with individual support (de Barcelos Silva et al., 2020; Knote et al., 2021). **Intelligence** (MC_3) in digital technology, is defined by a system's ability to perceive, learn from data, make autonomous decisions, and adapt to its environment (Boden, 2016; Brynjolfsson & McAfee, 2011; Turing, 1950). This encompasses essential qualities such as simulating human cognition including human-like emotions (anthropomorphism), gaining new knowledge through interaction or training (learning ability), maintaining contextual awareness of interactions and surroundings (context awareness), and modifying behavior in response to new information (adaptability) (Gunkel, 2012; Hengstler et al., 2016; Nilsson, 2009; Russell, 2016). These attributes distinguish intelligent systems from traditional technologies which are mostly rule-based and pre-defined (Gignac & Szodorai, 2024). Context awareness (D_{31}) defines a DAT's ability to incorporate contextual information into interactions. Systems with low context awareness (C_{311})

operate strictly based on predefined parameters, without considering past interactions or real-time inputs. More advanced DATs (C_{312}) dynamically adapt to ongoing interactions, integrating past exchanges and situational cues to personalize responses (Abowd et al., 1999; Noonia et al., 2024). The degree of anthropomorphism (D_{32}) captures the extent to which DATs exhibit human-like qualities (Kim & Im, 2023). It ranges from low anthropomorphism (C_{321}), where the system lacks human-like features, to high anthropomorphism (C_{322}). According to (Epley, 2018), DATs are »humanized« through features such as physical traits (e.g., voice) along with personality and emotional expressions. Environmental adaptability (D_{33}) reflects a DAT's ability to recognize and respond to contextual changes such as user behavior, location, or ambient conditions. Less adaptable systems (C_{331}) rely on static, predefined responses, while adaptive systems (C_{332}) anticipate user needs and modify their functionality accordingly (Akata et al., 2020; Pais et al., 2015). Learning ability (D_{34}) evaluates a DAT's capacity to acquire, adapt, and apply knowledge. It spans from predefined knowledge (C_{341}) (Gignac & Szodorai, 2024), where the DAT relies entirely on static predefined knowledge or datasets, to rudimentary (C_{342}) (Weizenbaum, 1966), which involves basic adjustments, and extensive (C_{343}) (Noonia et al., 2024), characterized by advanced self-learning capabilities that enable the system to adapt, evolve, and enhance interactions over time (Nilsson, 2009; Turing, 1950). This ability is critical for improving knowledge and delivering increasingly effective and personalized interactions (Rashid & Kausik, 2024). Interaction (MC_4) explores how DATs engage with users, focusing on appearance, input modes, initiative, and the number of users addressed. This dimension highlights the methods and modalities that shape user visual experience and accessibility (Kim & Im, 2023; Noonia et al., 2024). Appearance (D_{41}) in DATs ranges from no appearance (C_{411}), where the assistant operates invisibly without a visual representation, to low appearance (C_{412}), characterized by robot-like features, limited gestures, and blank facial expressions. High appearance (C_{413}) at DATs include human-like avatars with smooth hand gestures and varied facial expressions, such as smiling and mimicking emotions (Alabed et al., 2022; Kim & Im, 2023). Initiative (D_{42}) in DATs describes the level of control over the interaction flow, ranging from delegated (C_{421}), where users initiate and direct all interactions, to mixed (C_{422}), where control is shared, with the DAT occasionally offering suggestions or taking action based on context (Angin et al., 2018; Kugele et al., 2021). At the highest level, autonomous (C_{423}), the DAT independently initiates interactions, anticipates needs, and adapts dynamically to changes, showcasing proactive and context-aware capabilities (Jiang & Arkin, 2015). Input (D_{43}) in DATs defines how the system receives input from users or other entities, ranging from text-based (C_{432}) inputs, such as chat typing, to visual/gesture-based (C_{432}) commands involving gestures, emotional expressions or visual cues. It also covers voice or speech (C_{433}) inputs using spoken language, multiple (C_{431}) inputs combining various modalities for enhanced flexibility (Kiseleva et al., 2016; Rubio-Drosdov et al., 2017; Wellsandt et al., 2021; Zhu et al., 2014). Number of users addressed (D_{44}) in DATs defines the system's capacity to interact with one or multiple users simultaneously and how the experience differs for each user. It indicates whether the DAT operates in a 1:1 setup (C_{441}), focusing on individual interactions, or a 1-to-many setup (C_{442}), managing interactions across multiple users concurrently (Noonia et al., 2024). User interface (D_{45}) in DATs refers to the platform or medium enabling user interaction with the system. It includes app (C_{451}), where interaction occurs via a dedicated application; device (C_{452}), where the DAT is embedded in a physical device, such as a smart speaker; multiple (C_{453}), where the DAT operates seamlessly across various platforms or devices; proprietary software (C_{454}), which relies on custom-built interfaces tailored to its ecosystem; and website (C_{455}), where interaction is facilitated through an interface built into a website (Klopfenstein et al., 2017; Knote et al., 2019; Noonia et al., 2024; Valtolina et al., 2020).

4.2 Taxonomy evaluation

Our evaluation employs morphological field analysis (Ritchey, 2011; Rittelmeyer & Sandkuhl, 2023) to validate the taxonomy's effectiveness in classifying DATs and addressing terminology inconsistencies (see online Appendix[1]). This approach is particularly relevant for DATs, which frequently recombine patterns in their application, perception, and implementation (Knote et al., 2019; Rittelmeyer & Sandkuhl, 2023). The assistant concept encompasses five DATs (VAS, VA, IVA, DA, and IPA), revealing significant terminology overlap. For instance, while IPA and IVA both target individual users, they lack distinctive characteristics even in areas their names suggest (e.g., »personal« applicability or advanced intelligence).

[1] https://doi.org/10.6084/m9.figshare.28330274.v1

One clear distinction emerges with VA, which is uniquely defined by exclusive voice input functionality, providing a legitimate taxonomic differentiation (Brachten et al., 2020; Ki et al., 2020; C. Li et al., 2023; Porra et al., 2020; Ripa et al., 2023). Chatbot (30% of our sample; Preiß & Westner, 2025). follow a simpler structure, mainly split between »chatbot« and »AI chatbot.« As AI has become standard, the »AI« modifier is now redundant. ChatGPT, though often labeled a chatbot, functions more like an assistant due to GAI and multimodal capabilities (Khennouche et al., 2024; Okey et al., 2023), distinguishing it from traditional customer-service chatbots (Ayers et al., 2023; Caccavale et al., 2024). The agent concept (29% of the sample, Preiß & Westner, 2025), shows excessive overlap, with IA, AI agents, and VAG largely indistinguishable in function. For example, CA and CAIA demonstrate identical morphological patterns, supporting their treatment as synonymous terms (Adamopoulou & Moussiades, 2020; Alabed et al., 2022; Ashfaq et al., 2020).

4.3 Synthesis and Integration

Validating the findings, we synthesized the three concepts into a unified visualization (Figure 2), which maps their manifestations within the taxonomy. This synthesis reveals that while distinct patterns emerge for each concept, significant overlap exists in certain characteristics and modifiers like »AI,« »intelligent,« and »personal« are often used interchangeably (Knote et al., 2019; Pais et al., 2015), confirming the need for more precise terminology. This empirical validation demonstrates our taxonomy's effectiveness in: Clarifying distinctions between core concepts, identifying redundant terminology, providing a framework for consistent classification, and supporting more precise naming conventions for future DAT development. The taxonomy also aids decision-making by helping practitioners align the terminology with the appropriate framework. For example, the process begins by identifying the underlying concept being targeted (assistant, chatbot, or agent), followed by determining the dominant differentiator—whether a technical aspect or a contextual element. Moving forward, the use of DAT terms will be more systematic, reducing variability and focusing on a single defining characteristic, such as »virtual« or »voice,« to ensure consistency and clarity in classification.

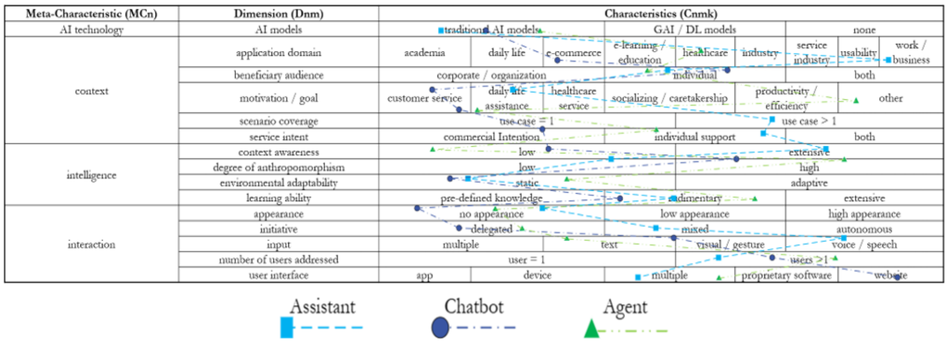

Figure 2: Visualization of the three main concepts within the taxonomy as a morphological field

Source: Own

5 Discussion & Conclusion

The findings from the morphological fields highlight jingle-jangle fallacies, where identical terms represent distinct concepts, and similar terms denote different functionalities (Marsh et al., 2019). To address this, the taxonomy is structured around four meta-characteristics: AI technology, context, intelligence, and interaction, further divided into 15 dimensions and 52 characteristics, ensuring clarity and consistency. Testing on chatbots, agents, and assistants confirmed the taxonomy's ability to clarify distinctions and address terminological inconsistencies from the morphological field analysis. Academically, the taxonomy establishes a unified framework that resolves overlapping and redundant terminologies, such as the conflation of IPA and VA or the overuse of »intelligent.« It supports comparative studies, theory-building, and systematic identification of research gaps by categorizing DATs into well-defined meta-characteristics. Practically, the taxonomy serves as a decision-making tool for aligning DAT functionalities with organizational goals and contexts. For RQ1, effective classification requires both technical (AI models, learning capabilities) and contextual (application domains, interaction modalities) elements. Regarding RQ2, the taxonomy enhances conceptual clarity and practical usability, bridging theoretical and practical gaps while addressing jingle-jangle fallacies (see Figure 1). Despite a rigorous methodology (Nickerson et al., 2013), general validity remains a challenge due to the rapid evolution of DATs. Subjective choices in defining dimensions and ending conditions (Nickerson et al., 2013) also influence its structure, and an empirical approach (e.g., developer interviews) could offer alternative insights. The focus on GAI-based DATs may have narrowed findings, and excluding terms like bot and multi-agent systems (Preiß & Westner, 2025), could limit relevance to specific fields. Future research should broaden the technological scope and validate the taxonomy across varied sectors and emerging technologies, as current findings are primarily based on recent proprietary GAI-based DATs. Exploring interrelations among meta-characteristics and their impact on DAT development and adoption is essential. Harmonizing existing DAT classifications can also address terminology inconsistencies and enhance coherence. As technological innovations continue, the taxonomy must evolve, highlight the necessity of regular updates to the taxonomy as it »may be a moving target« (Nickerson et al., 2013, p. 341).

Data availability. Additional data in form of an online appendix is provided here: https://doi.org/10.6084/m9.figshare.28330274.v1

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