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From Agents to Copilots: A Systematic Review of Digital Assistant Technology Adoption in Proprietary Productivity Software

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***Abstract*—This study provides a systematic review of how the impact and adaptation of digital assistant technologies (DATs) are defined, operationalized, and studied, synthesizing key domains where DATs generate or are expected to generate value. Based on an analysis of 61 articles published since 2013, it identifies five main areas of impact: productivity and efficiency, business development, resource optimization, quality enhancement, and the promotion of learning and creativity. The review highlights DAT adoption across various disciplines and industries, while revealing limited longitudinal research on benefits and adaptation. Key gaps remain in understanding strategic use and sustained impact. Future research should explore longitudinal comparisons of recently introduced generative AI-driven DATs and their organizational implications. This review contributes to information systems research by structuring current knowledge on DAT adoption and outcomes, and by proposing a research agenda to support deeper exploration of their value and long-term integration.**

***Index Terms*—DATs, SLR, generative artificial intelligence, assistant, chatbot, agent, Copilot, Gemini, ChatGPT, productivity software.**

I. Introduction

DIGITAL assistant technologies (DATs)—such as intelligent agents, chatbots, and voice assistants—hold significant transformative potential for large enterprises by automating routine tasks, enhancing data-driven decision-making, and enriching user interactions across various business contexts [1]. The rapid breakthroughs in artificial intelligence (AI), particularly in generative artificial intelligence (GAI), have further amplified the capabilities of DATs sparking a competitive race among organizations to identify and leverage optimal use cases [2], [3], [4]. As a result, substantial investments are being directed toward AI-driven DATs aimed at enhancing productivity, efficiency, and strategic value [5]. These DATs enable automation, reduce non-value-adding or repetitive tasks, and improve user interactions across diverse business contexts. Despite their growing adoption and capabilities, particularly with the emergence of GAI, the specific mechanisms enabling organizations to capture productivity benefits from DATs remain insufficiently understood [1]. This research gap is particularly evident in widely adopted productivity platforms such as Microsoft 365 and Google Workspace, where DAT integration is in its early stages [6], [7]. These platforms dominate the productivity software market: as of February 2024, Google Workspace held over 44% of the global market, and Microsoft 365 approximately 30%, with some estimates exceeding 48%, representing over 345 million active paid users [8], [9], [10]. Given their market dominance, future academic research into these technologies is expected to yield substantial insights regarding their impact on productivity. Therefore, a critical—yet underexplored—area within IS research involves understanding how these technologies are embedded into everyday work processes and what factors influence their successful adoption.

Given these developments, it is also essential to examine how DATs were applied in the pre-GAI era, what impacts were studied, and how these insights can inform the integration of GAI-enhanced DATs within productivity software contexts today.

This systematic literature review (SLR) aims to synthesize and contextualize existing research on DAT adoption, identify key areas of impact, and articulate their operational and strategic implications for organizations. Beyond mapping the current knowledge base, it advances a research agenda that addresses pressing questions arising from the emergence of GAI in DAT-focused IS research. The following research questions guide the focus of this SLR:

- RQ1: How does existing literature evaluate and characterize the impact of DATs in organizational settings, particularly in terms of measurement, intended outcomes, and the reallocation of freed-up capacity?
- RQ2: How does existing literature examine the use of DAT in conjunction with proprietary productivity software in organizational contexts?

The study begins with background information, followed by methodology, findings (including bibliometric and data analyses), discussion addressing the research questions with critical reflections and recommendations. It concludes with key findings, implications, limitations, and a research agenda outlining thematic and methodological directions.

II. Research background

The recent proliferation of AI-related concepts—including machine learning, GAI, and transformer architectures—reflects their growing relevance across organizational contexts [1], [11]. Central to these developments are DATs, which encompass chatbots, intelligent personal assistants, virtual assistants (VA), and intelligent agents [12]. These technologies increasingly manifest in branded forms such as Gemini, Claude, and ChatGPT, illustrating the convergence of GAI

and DATs in organizational environments [13], [14], [15], [16]. GAI, as an advanced form of machine learning, generates novel content (e.g., text, images, audio, and video) by analyzing large-scale datasets [17]. GAI an advanced form of machine learning, has evolved with large language models (LLMs) like ChatGPT and Google Gemini, enabling the creation of novel text, images, audio, and video from large-scale data sets [6], [17], [18]. Unlike traditional predictive AI, it emphasizes creative generation and signals progress toward artificial general intelligence, enabling a wide range of potential use cases for organizations. With expanding multimodal capabilities, LLMs have become key drivers of innovation across sectors and are increasingly deployed through DATs in organizational contexts [1], [19]. Microsoft Copilot for 365 and Google Gemini for Workspace serve as VAs, highlighting the convergence of GAI and workplace productivity—reshaping workflows, enhancing collaboration, and transforming enterprise ecosystems [4], [12], [20], [21].

Productivity software—also known as office productivity software [22], [23]—extends beyond traditional tasks like text writing, spreadsheets, and presentations. It now encompasses intelligent collaboration, automation, and workflow orchestration—tools that are increasingly infused with GAI to support knowledge work at scale [24], [25]. The integration of GAI into productivity software represents a major paradigm shift [22]. Consequently, this study adopts the term "productivity software" to reflect this expanded functionality by products such as Microsoft 365 and Google Workspace.

III. Research Methodology

This section outlines the methodological framework guiding the SLR. The review systematically examines the literature within DAT research [27]. By aggregating and analyzing existing research, it provides an in-depth overview of the current scholarly discourse [28], [29]. Following the structure proposed by [30], the process unfolds in three phases: planning (i), review (ii), and dissemination (iii).

In the planning phase, the study's objectives and research questions—introduced in Chapter 1—are articulated to establish a clear conceptual basis. This phase also involves adopting structured, transparent, and replicable methods to identify, select, and evaluate relevant articles [30]. ensuring methodological rigor. The subsequent phases involve systematic data extraction and in-depth analysis [31], [32].

An initial search in the Scopus database yielded 5,469 articles. During the review phase (ii), iterative keyword and sample refinement using the PRISMA method narrowed the sample to 61 articles, prioritizing relevance and rigor [31]. In the dissemination phase (iii), data were extracted and synthesized, enabling critical interpretation of the findings.

ChatGPT-4o was employed to "identify synonyms, related terms, and language variations" [30, p. 87] for constructing the initial review sample, ultimately resulting in the manual creation of the final search string incorporating findings from [1].

IV. Planning the Review (I): Initial Review Sample

The initial search string was intentionally broad, focusing on keywords related to the three DAT concepts: assistant, agent, and chatbot [1]. Additional keywords such as "digital," "virtual," and "artificial intelligence" were included to define the scope and direction of the research [12]. Adjectives describing broader potential benefits of DAT applications were deliberately excluded to ensure neutrality, avoid bias, and minimize the risk of overlooking relevant research streams or topics. These keywords were specifically targeted within the title, keywords, or abstract of articles.

The search string was structured into two keyword buckets: one representing the DAT concept and the other indicating digital characteristics. The buckets were linked using AND for a systematic search, while keywords within each bucket were combined with OR (see Table I). The first bucket was designed to address jingle-jangle fallacies in the DAT domain, ensuring comprehensive coverage of all relevant research streams and preventing the exclusion of pertinent DATs due to inconsistent terminology [1]. We included journal articles for their recognized credibility [34], [35], [36], [37] and peer-reviewed conference proceedings for their role in providing early insights into emerging knowledge, particularly relevant to IS and GAI research [38]. To ensure comprehensive coverage, our search targeted German and English publications across all subject areas, capturing a wide range of industries benefiting from VA. Our focus was on articles and proceedings published after 2013, restricting the scope to completed research publications. To ensure the inclusion of all relevant and representative IS outlets in the initial sample, we utilized the '3XL' filter from Litbaskets.io, accessed on January 19, 2025, which is a curated set of 847 ranked IS journals [39]. Litbaskets.io effectively supports literature searches via Scopus, the largest multidisciplinary database [40], resulting in a total of 5,469 articles.

TABLE I
INITIAL SEARCH STRING

Basket 3XL / 847 essential IS journals	
searched in title, keywords, or abstract of a article or proceeding	
published after 2013 until January 19th 2025	
English / German only	
Keywords	
Technology **AND**	characteristic
agent* **OR** assistant* **OR** chatbot*	"artificial intelligence" **OR** digital **OR** virtual
5,469 articles	

We utilized VOSviewer 1.6.20 to examine the initial search results, creating visualization maps that depict articles and keywords as circles, where the size and proximity reflect activity levels and the strength of relationships [41]. A thesaurus file was used to standardize variations in spelling and plural forms of keywords (e.g., GAI/generative artificial intelligence, assistant/assistants). 37,415 unique keywords, grouping 1,552 (with a minimum occurrence of 10) into five distinct clusters based on co-occurrence patterns, as shown in Fig. 1. The analysis focuses on keywords related to RQ1—operational efficiency, workforce productivity, and business performance.

Cluster 1 (red) contains 778 items. The most prominent keyword in this cluster is "artificial intelligence," which appears 2,011 times with a total link strength of 19,020, indicating its central role in the research landscape.

A deeper examination of the keyword distribution highlights several terms associated with quality and efficiency. Notable terms include "quality of service" (569, occurrences: 65), "quality of life" (1,194, occurrences: 46), "health care quality" (416, occurrences: 16), "high quality" (97, occurrences: 13), "data quality" (238, occurrences: 11), and "image quality" (266, occurrences: 11). Efficiency is reinforced by "efficiency" (453, occurrences: 46) and "business process" (87, occurrences: 11), underscoring AI's role in optimizing operations and performance.

Cluster 2 (green) contains 442 items and is centered around the keyword "humans" (link strength: 25,335), which appears 1,180 times. Notably, despite having nearly half the occurrences of "artificial intelligence", this keyword exhibits a stronger link strength to other clusters. This extensive connectivity may stem from the focus of research on human-machine interaction.

Rather than presenting a unified theme, Cluster 2 consists of keywords commonly associated with human-machine interaction and healthcare digitization. The intensive linkage between Cluster 1 and Cluster 2 further emphasizes the high research focus and the growing significance of DATs, particularly in healthcare. This is reflected in key terms such as "chatbots" (link strength: 5,839, occurrences: 641), "conversational agents" (2,888, occurrences: 251), "personal digital assistant" (2,959, occurrences: 180), and "artificial intelligence chatbots" (797, occurrences: 62). Supporting this healthcare-driven focus are keywords like "health care" (2,226, occurrences: 132), "digital health" (2,432, occurrences: 101), and "communication" (2,118, occurrences: 112), all of which reinforce the relevance of AI-driven conversational technologies in the medical domain. The keyword "productivity"—appearing 11 times with a link strength of 156—is particularly relevant to the RQs and is positioned between Clusters 1 and 2 (within cluster 2). Its placement indicates the significance of productivity implications across both fields, further emphasizing DATs' potential impact.

Cluster 3 (blue), which contains 183 keywords related to research articles on molecular medicine and drug research.

Similarly, Cluster 4 (yellow) consists of 106 items and is centered around "algorithms" (link strength: 4,676, occurrences: 245). The primary theme of this cluster revolves around computer-aided or assisted diagnosis, as illustrated by keywords such as "computer-aided diagnosis" (446, occurrences: 24) and "computer-assisted diagnosis" (677, occurrences: 23). However, this cluster does not directly relate to the benefits of DATs in the context of large organizations.

Cluster 5 (purple), the smallest cluster with only 31 items, focuses on diabetes and potential treatments. However, its scattered position in the network indicates weak linkage to Clusters 1 and 2 and no significant relevance to the RQs. As a result, Clusters 3–5 were considered peripheral and filtered out.

The initial keyword analysis identifies terms for the final search query. With 5,469 articles, no content analysis was conducted, so keyword interpretations should be considered with caution. Still, three key insights emerge for refinement and expansion in the final search query:

- AI-related terms dominate, emphasizing its role in efficiency, quality, and business operations. Keywords such as "efficiency," "quality of service," and "business process" highlight AI's impact on optimizing workflows and enhancing productivity.
- Cluster 2 focuses on human-machine interaction, particularly in healthcare. Terms like "chatbots," "conversational agents," and "digital health" reflect the presents of DATs. Context analysis is needed to filter out peripheral medical topics.
- To ensure relevance, "quality," "efficiency," "productivity," and "business process" should be included in the next search string. These terms align with the RQs, help exclude irrelevant Clusters 3–5 and will help capture all relevant research streams.

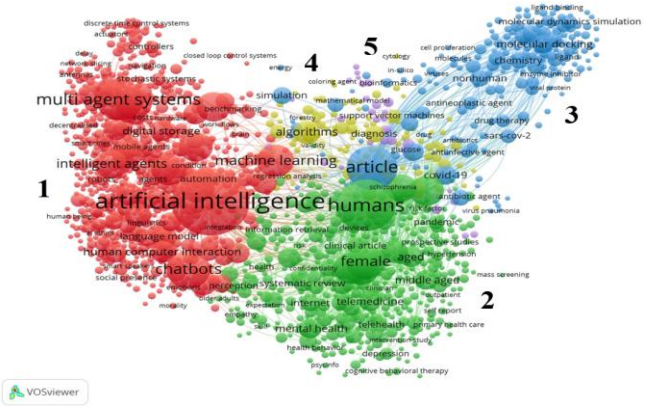

Fig. 1. Keyword co-occurrence network visualization - initial review sample (n= 5,469)

V. Performing the Review (II): Final Search Query

Based on the initial sample analysis, the final search string was refined with additional keywords, resulting in the query: ((agent* OR assistant* OR chatbot*) AND ("artificial intelligence" OR digital OR virtual) AND (quality OR efficiency OR productivity OR "business process*")). This refinement yielded a comprehensive dataset of 1,141 articles, exported on February 1, 2025. Following the PRISMA framework [31] (see Fig. 2), we performed a systematic selection process, including: (a) removal of duplicate or withdrawn articles, (b) screening of titles and abstracts based on predefined exclusion criteria, (c) a comprehensive full-text review to identify articles meeting the inclusion criteria, and (d) backward and forward citation searches to identify additional relevant articles [35], [37]. Following [34] we repeated the process for newly added articles until the sample achieved depth, consistency, and clarity.

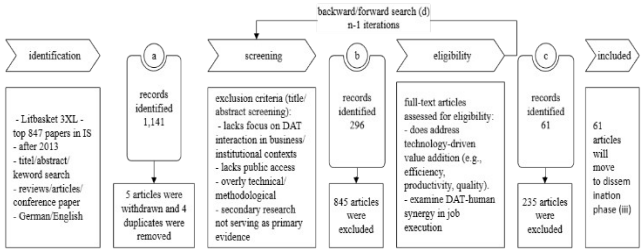

Fig. 2. Steps of the SLR with PRIMSA method according to [31]

VI. Dissemination (iii): Key findings & synthesis

A. Bibliometric Examination of the included dataset

The refinement process (see chapter V) yielded 61 articles containing 723 keywords, visualized in Fig. 3.This analysis identified three primary clusters: (1) DAT technologies and sales/customer service, (2) AI-related functional patterns and DATs, and (3) DAT and AI in research. The keyword 'artificial intelligence' emerged as the central node, serving as the nucleus and primary connector within this dataset.

This significance is driven by the pervasive integration of AI and GAI across various domains, which is "generating significant interest due to its potential to enhance personal efficiency" [4, p. 5]. The bibliometric analysis of the included sample reveals a steady increase in DAT adoption within corporate and institutional contexts. The number of relevant publications has grown from a single publication in 2019 to four in 2020, followed by seven in 2021 and six in 2022. Notably, a sharp increase was observed following the introduction of ChatGPT in November 2022 [18], with 13 publications in 2023 and 26 in 2024. Interestingly, in January 2025 alone, four articles have already been published, suggesting the potential for continued significant growth if this trend persists.

Keyword analysis. Conducting a keyword and co-occurrence analysis on the inclusion sample further reinforces a homogeneous pattern, as illustrated in Fig. 3. A total of 40 keywords met the threshold of three or more co-occurrences, with AI being the most prevalent term (40 occurrences). Notably, six distinct DATs were identified: chatbot (30), ChatGPT (14), artificial intelligence chatbots (4), intelligent assistants (4), conversational agents (4), VA (4), and intelligent agents (3). Copilot for M365 and Gemini for Google Workspace were not present in the key-word co-occurrence analysis. Collectively, these DAT terms account for 23.8% of the full co-occurrence sample. In relation to RQ1, the analysis further identified four keywords representing distinct measures for evaluating the potential impact of DAT integration within the final sample: efficiency (4), accuracy (3), high quality (3), and quality of service (3). These terms emphasize key dimensions in assessing the effectiveness and performance of DAT adoption across different contexts. Notably, productivity no longer appeared as a keyword in this sample.

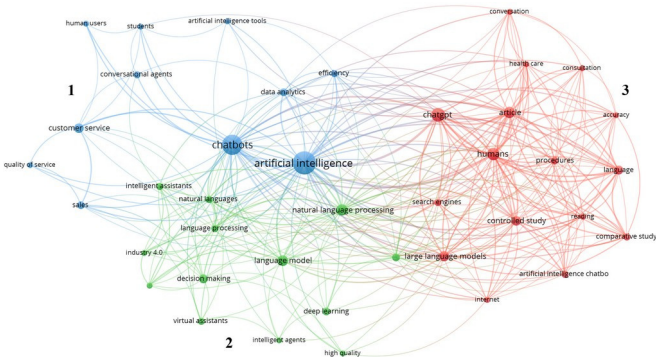

Fig. 3 Keyword co-occurrence network visualization (n=61 articles)

Documents by outlets. The examination of document types revealed the following distribution: journal articles (47; 77%) and conference papers (14; 23%). The prevalence of journal articles suggests that the topic has been extensively studied within a short period of time (since 2019), indicating strong scholarly engagement in the field [42]. The 61 publications analyzed were spread across 47 distinct outlets (see Table II). The top three publication outlets were the Journal of Medical Internet Research (6 articles; 15.4%), IFIP Advances in Information and Communication Technology (3 articles; 7.7%), and CEUR Workshop Proceedings (3 articles; 7.7%). This distribution underscores the interdisciplinary nature of the research, with contributions spanning medical informatics, information and communication technology, and other IS outlets. This emphasis likely accounts for the human-centered cluster 3 in Fig. 3, which highlights extensive research on human-machine interaction and healthcare.

Table II

Distribution of journals by total count and citation sum in the final sample (count >2)

Journal	Count		Sum citations/journal	
Journal of Medical Internet Research	6	9.8%	87	11.9%
IFIP Advances in Information and Communication Technology	3	4.9%	9	1.2%
CEUR Workshop Proceedings	3	4.9%	4	0.5%
Lecture Notes in Business Information Processing	2	3.3%	12	1.6%
International Journal of Medical Informatics	2	3.3%	16	2.2%
International Conference on Software Business	2	3.3%	2	0.3%
Expert Systems with Applications	2	3.3%	74	10.1%
Electronic Commerce Research and Applications	2	3.3%	4	0.5%
Other 39 journals count < 2	39	63.9%	734	77.9%
Total	61	100.0%	942	100.0%

Co-Authorship and author analysis. The analysis identified the key contributors within this sample, revealing that only 13 researchers had at least two co-authorships, defined as collab-

orative efforts between scholars contributing to the same publication. This group represents less than 12% of the total 285 authors in the dataset. Notably, these 13 researchers accounted for 43.7% of the total citation count, with Yu Chen having two co-authorships and 200 citations. The small number of scholars with >1 article underscores a potential gap indicating that relatively few researchers are consistently contributing within the domain. Among the 285 contributors, only one network is linked through six publications, primarily due to the work of Massimo Mecella. His research encompasses conversational agents in business process models [43], chatbots in digital factories [44], and an assistant for legal users [45]. The scarcity of strong interconnections and collaborative efforts among re-searchers highlights a highly segmented field with limited cooperation [46]. From an article perspective, the top 15 most influential publications in the sample account for 811 citations, representing 86.1% of the total 942 citations. Online appendix Table I highlights these key contributions, illustrating their impact on the overall sample through substantial citation counts. Overall, the absence of strong connections between authors, as indicated by link strength, may suggest a lack of collaborative research efforts within the DAT domain.

B. Data Analysis of existing literature

Data analysis – type of research. We analyzed the sample and present an overview of the research design and approach in Table III, with article-level details illustrated in Fig. 4 [47]. The findings reveal a strong emphasis on empirical research, with 56 articles (91.8%) adopting empirical approaches. Among these, quantitative designs are most common (26/42.6%), typically aligned with positivist (21/34.4%) and post-positivist (11/18.0%) worldviews (see Fig. 4), reflecting a focus on objectivity, measurement, and causal inference.

TABLE III

OVERVIEW OF RESEARCH DESIGN AND APPROACH

Design	count	Research approach	count
Quantitative	26	experimental	14
		survey	6
		comparative assessment	5
		interviews	1
Qualitative	15	experimental	4
		design science res.	3
		case study	2
		interviews	2
		co-design study	1
		comparative assessment	1
		survey	1
		systematic mapping	1
Mixed method	15	design science res.	6
		experimental	4
		convergent parallel	2
		exploratory sequential	2
		comparative assessment	1
Non-empir.	5	design science res.	3
		conceptual analysis	1
		practise-based	1

Notably, not a single study employed longitudinal research design. Despite the dominance of empirical methods, all 61 articles relied on alternative research approaches, as detailed throughout this chapter. This absence of longitudinal inquiry highlights a significant gap in understanding the sustained use, adaptation, and long-term impact of DAT within real-world contexts [48]. It underscores the importance of future research that extends beyond immediate performance metrics to investigate how users, systems, and organizational environments co-evolve over time.

Qualitative designs (15/24.6%) show stronger ties to interpretivist perspectives (7/11.5%), aiming to capture contextual depth and user experiences, though still secondary in representation. Mixed methods articles (15/24.6%) often reflect a pragmatist worldview (22/36.1%), blending quantitative and qualitative paradigms to pursue practical, problem-solving goals. The dominance of pragmatist and positivist orientations (shaped by inclusion criteria) reflects a focus on outcome-driven research, emphasizing quantifiable data and replicable cause-and-effect relationships [49]. The remaining non-empirical research (5/8.2%)—including design science, conceptual analysis, and practice-based work—supports theoretical exploration and methodological innovation, though it remains limited in volume. Overall, the analysis reflect a field focused on solution-oriented inquiry, emphasizing real-world performance, usability, and iterative refinement of DAT [50], [51].

While empirical inquiry dominates, the limited use of established IS theories reinforces the field's developmental stage. Only four articles explicitly employed IS theories, further underscoring this empirical orientation [52]. These include the Technology Acceptance Model (TAM) and DeLone & McLean IS Success Model [53], the Decomposed Theory of Planned Behavior [54], Fit-Viability Theory [55], and Attribution Theory [55]. The limited use of theory reflects the field's exploratory, application-driven nature, where technical feasibility often takes precedence. However, as DAT become more embedded in daily life, the growing uptake of IS theories since 2021 signals a timely shift toward deeper conceptual integration and a stronger focus on adoption. [52].

Notably, purely secondary research (e.g., SLRs, taxonomies, or frameworks) was excluded in the PRISMA process. In sum, research on DAT is empirical, pragmatic, and impact-driven, with a clear focus on performance and usability. However, the limited use of IS theories and interpretive lenses signals a need for deeper conceptual grounding and contextual insight [50].

Data Analysis – Concepts and DAT used in final sample. We further analyzed the concepts and technologies referenced in each publication to understand their application across various domains and use cases. Our review found that the assistant concept appears 34 times (55.7%), making it the most prevalent, followed by the agent concept, which is featured in 22 articles (36.1%). Some articles discuss multiple concepts or DATs, which is why the total does not sum to 61 in the more detailed Fig. 4. For example, Copilot and Gemini fall

Reference	Entity		Segment/industry																	User group																								DAT concept studied									AI technology							Research setup			
Reference	corporate	institutional	academia	automotive	process management	construction	e-commerce	education	finance	general	healthcare	insurance	justice	logistics	manufacturing	marketing	public sector	social media	software development/coding	authorities	banker	business decision maker	customer service	customer service/sales agents	dentistry staff	engineers	knowledge worker	legal users	librarian	manufactoring worker	market maker	medical staff	mental health staff	patients	platform providers/content moderation	process designer	programmer	purchaser/buyer	questioner	researcher	students	teaching staff	trader	assistant	agent	chatbot	assistant Bard	assistant ChatGPT	assistant Claude	assistant Copilot	assistant Gemini	assistant Bloomz	DL	GAI	ML	NLP	RL	SL	unspecified	Philosophical worldview	Research design	Reserach approach	# Total quant sample size
Almeida (2025)	x															x											x																			x									x	x				PR	MM	DS	-
Alomair et al. (2024)		x								x																	x																				x	x							x						PO	MM	CO	13
Arsovski et al. (2022)	x									x																	x																			x							x		x	x				PPO	QT	E	12k
Baabdullah (2024)	x									x																	x																				x	x							x						PO	QT	S	228
Belhaj et al. (2021)		x						x																															x							x									x	x				PR	QT	CO	70
Ben-shabat et al. (2022)		x									x																					x														x									x	x				PPO	QT	E	224
Bird & Lotfi (2024)	x									x													x																							x							x		x	x				PO	MM	E	19
Boubker (2024)		x						x																																	x							x						x						PO	QT	S	319
Bouras et al. (2024)	x																x						x																							x									x	x				PO	QL	E	-
Brachten et al. (2021)	x									x																	x																	x															x	PO	QT	S	198
Calisto et al. (2021)		x									x																					x												x									x			x		x		PO	QT	E	45
Chen et al. (2022)		x						x																																		x				x									x					PR	MM	DS	195
Chen et al. (2023)	x									x														x																				x										x						PPO	QT	S	415
Cheng et al. (2023)		x	x																																					x								x						x						PPO	QT	E	30
Colabianchi et al. (2024)	x														x															x														x										x						PPO	MM	E	30
D. Kudryavtsev (2023)	x									x												x																						x										x						PR	MM	DS	-
De Luzi (2023)	x												x															x																x										x						I	MM	DS	-
Ding et al. (2021)	x						x																x																							x													x	PR	QL	DS	-
Dong et al. (2024)	x																		x																		x											x						x						PO	QT	E	-
Dursun & Bilici Gecer (2024)		x									x																					x																x		x	x			x						PPO	QT	CO	20
Eberhart et al. (2020)	x																		x																		x							x													x			PO	MM	E	30
Vicente et al. (2023)	x								x																						x														x									x						PPO	QT	E	121
Figliè et al. (2024)	x														x															x														x										x						PR	MM	DS	
Fikardos et al. (2024)	x			x																						x																		x											x	x				PR	QL	DS	-
Giannakopoulos et al. (2023)		x									x														x																						x	x		x	x			x						PO	QL	E	-
Graham et al. (2025)	x								x												x																									x									x	x				PR	QL	CO	45
Guo et al. (2023)		x						x																																	x					x										x				PO	MM	E	88
Hirchoua et al. (2021)	x								x																																		x		x												x			PO	QT	E	-
Jackson & Panteli (2024)	x									x																	x																	x		x							x	x		x				I	QL	I	26
Kocaballi et al. (2020)		x									x																					x												x											x	x				PR	QL	CD	16
Köster et al. (2023)	x													x													x																	x															x	PR	MM	DS	-
Kuhail et al. (2024)		x									x																						x													x								x						PO	QT	E	63
Lewandowski et al. (2023)	x									x																	x																		x										x	x				PR	MM	CP	13
Lin et al. (2024)	x						x																x																							x							x			x				PR	MM	CP	-
Mcgowan et al. (2024)		x									x																					x															x							x						PPO	QT	CO	-
Melnyk et al. (2024)	x									x																	x																			x										x		x		PR	QL	DS	-
Mesenzani & Di massa (2021)	x									x														x																						x							x		x	x				PR	QL	S	30
Millam & Bakke (2024)	x																		x																		x											x		x				x						PR	QT	E	10
Mosquera et al. (2024)	x																		x																		x							x											x	x				PO	QL	SM	58
Mydyti & Kadriu (2021)	x									x																	x																			x							x			x				PO	QL	C	-
Nadeem et al. (2024)		x																x																	x									x										x						PR	QT	E	1k
Nascimento Tei. et al. (2024)		x									x																										x											x						x						PPO	QT	CO	150
Pival (2023)		x	x																										x																			x		x				x						PR	NE	P	-
Rice et al. (2024)		x	x																																					x				x										x						I	NE	P	-
Rooein et al. (2020)	x														x															x																x										x				PPO	NE	DS	-
Rooein et al. (2022)	x				x																															x										x										x				PR	NE	DS	-
Siddig & Hines (2019)	x										x																					x														x									x	x				I	MM	ES	20
Solohubov et al. (2024)		x																	x																		x											x		x				x						PR	QL	E	-
Sonntag et al. (2023)	x			x																			x																							x										x				PR	QT	I	158
Stephan et al. (2024)	x										x																					x																x						x						PR	QT	E	100
Wang et al. (2025)	x										x																					x																x						x						PR	MM	ES	390
Waseem et. Al (2024)	x									x																												x						x										x						I	MM	DS	-
Wellsandt et al. (2022)	x														x															x														x											x	x				I	QL	C	-
Wilhelm et al. (2023)		x									x																					x																x	x			x		x						PO	QT	CO	240
Yau et al. (2024)		x									x																							x													x	x	x	x				x						PPO	QT	E	1.2k
Yum et al. (2022)	x											x											x																						x										x					PR	QL	I	10
Yun et al. (2023)	x										x																					x																x						x						PO	QL	E	10
Zhang et al. (2024)	x									x																	x																			x													x	PO	QT	S	399
Zhang et al. (2024)	x						x																x																							x										x		x		PO	QT	S	508
Zhao et al. (2025)		x									x																					x												x									x							PO	QT	E	30
Zhong et al. (2020)	x					x														x																										x							x			x				PO	QT	E	200
Total	40	21	3	2	1	1	3	4	3	14	15	1	1	1	4	1	1	1	5	1	1	1	7	2	1	1	11	1	1	4	1	11	1	1	1	1	6	1	1	2	2	1	1	18	4	23	5	16	2	6	2	1	9	28	16	25	2	3	4				

Worldviews
I: Interpretivist
PPO: Postpositivst
PO: Positivist
PR: Pragmatist

Reserach design
MM: Mixed method
NE: Non-empricial
QL: Qualitative
QT: Quantitative

Reserach approach
C: Case study
CP: Convergent parallel
CD: Co-design study
CO: Comparative assessment
E: Experimental reserach
ES: Exploratory sequential
G: Grounded theory
DS: Design science
I: Interview reserach
P: Prototyping
S: Survey reserach
SM: Systematic mapping

AI technology
DL: Deep learning
GAI: Generative AI
ML: Machne learning
NLP: Natural lang. proc.
RL: Reinforcement learning
SL: Supervised learning

Fig. 4. Literature coding results

under the broader concept of assistants but have been researched separately. The strong presence of chatbots is closely tied to their widespread adoption in healthcare, e-commerce, and customer service, as explored before [1]. Copilot (formerly BingChat) and Gemini, identified in Section 2.1 as freely accessible, browser-based proprietary LLMs, differ from the tools discussed in Section 2.2, which are embedded within Microsoft's and Google's productivity software and operate within organizational data environments. Given this distinction, DATs operating within productivity software are not represented in the sample. The only GAI-enhanced software included is Miro, a collaborative whiteboarding tool incorporating an LLM [56]. Overall, proprietary GAI-driven DATs—such as ChatGPT, Gemini, Copilot, and Bard—appear in 17 cases (27.9%), highlighting their growing significance since 2023.

Data analysis – Research themes. For the content coding of research themes, we classified data into the categories of "entity," "segment/industry," and "user group." The application of theme categorization follows established practices in IS literature reviews (e.g., [57], [58]). To enhance granularity, we applied an open coding approach [59]. The resulting classification (see Fig. 4), aligns with the concept matrix framework [37]. The analysis of 61 research articles identifies two primary application contexts: corporate (65.6%) and institutional (34.4%). This division supports comparative insights

into how each segment adopts and prioritizes DATs—particularly valuable for future research focused on specific sectors, such as large enterprises. 17 industries or segments were also identified, listed alphabetically by frequency. Fig. 4 presents the coded matrix of user groups within their respective application domains. The distribution in Fig. 4 underscores the multidisciplinary scope of DAT applications, with healthcare and general applications as the dominant domains, followed by software development/coding, education, and manufacturing. The term general (14/23%) encompasses publications with a broad scope, spanning multiple industries, general applications, or lacking a distinct focus. The most prominent industry-specific fields are healthcare (15/24.6%) and software development/coding (5/8.2%). Together, these three fields account for 34 (55.7%) of the total sample, illustrating the primary domains of the researched domain. However, a significant portion of the re-search remains broad and use-case unrelated, categorized under "general." This imbalance may suggest a need for more specialized research to generate deeper insights across various fields and broaden the understanding beyond the dominant healthcare domain.

Fig. 4 also illustrates the distribution of user groups addressed by the DAT, along with their respective counts and percentages. The most present user groups overall are knowledge workers (11/18.0%), medical staff (11/18.0%), and customer service (7/11.5%) which includes the single-occurrence customer service and sales agent group. In the corporate sector, knowledge workers dominate (10/16.4%), followed by customer service roles (7/11.5%), which exist exclusively in the corporate environment in this sample. The institutional sector is primarily driven by healthcare-related professionals (9/14.8%), though healthcare also appears in the corporate sector with 4 occurrences (6.6%), indicating its cross-sector relevance. Interestingly, DATs are also well established in supporting both institutional and corporate users in programming and software development (6/9.8%) across multiple domains, highlighting their significance in technological and digital advancements.

From a technology perspective, corporate research primarily focuses on assistants (18/45%) and chatbots (17/4%), which together represent 88% of articles in this category. One study examined both concepts jointly. Agents (4/10%) play a minor role in corporate research. A similar but more pronounced trend is observed in institutional research, where assistants account for 76% of articles and chatbots for 24%, primarily in healthcare, academia, and education. Agents are absent in institutional research, as they typically operate within clear and closed boundaries, handling structured tasks [5]. A detailed list of DAT occurrences in each article and its corresponding domain is provided in Fig. 4.

VII. Main findings

This section represents the core contribution of this SLR, synthesizing key findings on DAT applications, their intended functions, and the metrics and objectives guiding their implementation. It directly addresses RQ1 and RQ2 by examining the distinct characteristics of DAT utilization across the 61 analyzed articles. Table IV provides a structured overview of the five focus clusters identified through open coding, which were subsequently categorized into five application goal clusters using axial coding [60]. Each of these clusters is further explored and described in the following sections. The most prevalent subcategory, efficiency/quality, was examined in 13 articles and is analyzed in greater detail in online appendix Fig. 1. The categories will be briefly outlined, with an emphasis on the key measures that define them. Since some subcategories combine multiple measures within individual articles, not every specific combination will be discussed separately. However, their occurrence has been systematically coded within the analyzed articles.

Productivity & efficiency. Productivity and efficiency form the most dominant cluster (32/52.5%), serving as key drivers in business and institutional settings by optimizing resource use, accelerating operations, and availability [28, 65]. A major focus is efficiency and quality (13/21.3%), where DATs streamline processes while maintaining high standards, reducing manual effort and improving accuracy [61]. For example, Calisto et al. (2021) examined the impact of DATs on workflow efficiency and diagnostic quality in breast cancer [62], while Belhaj et al. (2021) demonstrated how such technologies can enhance the quality and efficiency of student-oriented services [63]. Productivity (9/14.8%) is closely linked, as DATs boost output by minimizing inefficiencies and accelerating task execution [5]. Brachten et al. (2021) argue that "chatbots should be positioned as personal technologies designed to support users and enhance productivity" [49 p. 11]. Efficiency (5/8.2%) reflects the role of DATs in eliminating bottlenecks and optimizing workflows, particularly in enterprise automation [28]. Some articles highlight a combined impact on efficiency and productivity (2/3.3%), where DATs simultaneously reduce resource waste and enhance overall performance [66]. Beyond speed and optimization, efficiency and effectiveness (1/1.6%) emphasize DATs' role in enhancing goal achievement and adaptive decision-making [67]. Finally, productivity and health protection (1/1.6%) highlight how DATs support both output and worker well-being [68].

Business growth & development. Business growth and development emerges as the second most prominent cluster (14/23%), underscoring the pivotal role of DATs strategic business expansion, decision-making, and revenue optimization. By facilitating value-driven tasks, business scalability, and cost efficiency, DATs enhance organizational competitiveness [44], [64], [65]. A key application goal within this cluster is enhancing focus on value-added tasks (7/11.5%) by reducing redundant activities, thereby improving overall performance, quality, and work-load efficiency. De Luzi (2023) finds that ChatGPT reduces processing time in legal work, freeing up time for higher-value tasks [45]. By automating mundane tasks, DATs enable employees to prioritize strategic and creative functions over routine administrative work, fostering innovation and workforce optimization, particularly in

knowledge-intensive industries [45], [66]. Closely linked, decision-making support, efficiency, and quality (3/4.9%) reflects DATs' capacity to enhance analytical capabilities, enabling organizations to navigate dynamic market conditions with optimized strategies [56], [67]. Kudryavtsev (2024) states that AI assistants enhance business development by accelerating design processes, lowering decision-making risks, and offering accessible, professional-level support [56]. Business expansion and development (2/3.3%) highlights DATs' contributions to scalability, market entry, and operational agility [56], [68]. The financial impact is evident in revenue growth and cost reduction (2/3.3%), where AI-driven insights and automation maximize profitability while minimizing expenses [54], [69].

Cost & resource optimization. Cost & resource optimization (7/11.5%) remains a critical objective, ensuring organizations maximize output while minimizing financial and operational inefficiencies. DATs support these goals through automation, predictive analytics, and streamlined processes, leading to enhanced cost efficiency and resource utilization [12]. Capacity increase (3/4.9%) highlights how AI-driven automation enables organizations to handle higher workloads without proportionally increasing resources, fostering scalability in customer service, operations, and production [14], [21], [70]. Cost reduction (3/4.9%) underscores DATs' role in eliminating inefficiencies, automating repetitive tasks, and optimizing resource allocation, significantly lowering operational expenses [71]. Bird and Lotfi (2024), for example, strengthen the narrative that chatbots in customer service are more cost-effective than fully human-operated models[72]. Organizations integrating intelligent automation in HR, finance, and customer service achieve substantial reductions in labor costs and time-intensive processes (cost-)effectiveness/process automation (1/1.6%) further demonstrates how DATs enhance efficiency through intelligent workflows, reducing manual interventions and improving process standardization across business functions [64].

Quality. The quality cluster (4/6.6%) highlights the role of DATs in enabling and maintaining higher standards across products, services, and decision-making. DATs enhance quality (2/3.3%) by automating tasks, minimizing human errors, enabling data-driven decisions, and accelerating creativity [73]. The combined category of quality and productivity (2/3.3%) emphasizes the dual impact of DATs in enhancing service reliability while optimizing operational efficiency [74]. Chen et al. (2023) confirm that AI chatbots improve service quality, thereby strengthening customer loyalty and driving business success [75].

Creativity and learning. The creativity and learning cluster (4/6.6%) highlights the expanding role of DATs in knowledge work, idea generation, and creativity enhancement. These technologies lower entry barriers to learning and support continuous professional development [76], [77], [78]. Creativity and efficiency (2/3.3%) enabled by DATs enhance ideation, design, and content creation while streamlining workflows and reducing cognitive load, driving faster innovation and execution [65], [79]. Cheng et al. (2023) positively evaluated the use of AI to increase efficiency in abstract writing for preclinical research [80]. Similarly, learning (2/3.3%) leverages AI-powered training to support skill development, personalized learning, and adaptive programs, improving feedback and knowledge retention by, for example, reducing language barriers and enhancing content accessibility [53], [81].

TABLE IV

KEY FOCUS AREAS OF DAT APPLICATION

Productivity & efficiency (32/52.5%)	**Business growth & development (14/23%)**
Efficiency/quality (13/21.3%)	Focus on value added tasks (7/11.5%)
Productivity (9/14.8%)	Decision making support/efficiency/quality (3/4.9%)
Efficiency (5/8.2%)	Business expansion/development (2/3.3%)
Efficiency/productivity (2/3.3%)	Revenue growth/cost reduction (2/3.3%)
Efficiency/effectiveness (1/1.6%)	**Quality (4/6.6%)**
Efficiency/quality/productivity (1/1.6%)	Quality (2/3.3%)
Productivity/health protection (1/1.6%)	Quality/productivity (2/3.3%)
Cost & resource optimization (7/11.5%)	**Creativity & learning (4/6.6%)**
Capacity increase (3/4.9%)	Creativity/efficiency (2/3.3%)
Cost reduction (3/4.9%)	Learning (2/3.3%)
(cost-)effectiveness/process automation (1/1.6%)	

VIII. RESEARCH AGENDA

Based on the five main focus areas identified through our SLR, we propose a research agenda that highlights key gaps and formulates future research questions within the most relevant and emerging research streams (see Fig. 5). Our analysis shows that the adoption of GAI-driven DATs hold the potential to reshape productivity, efficiency, business models, and strategy [55], [82], [83]. However, a critical gap remains: the lack of empirical, longitudinal evidence on the impact of DATs. While many articles focus on DAT implementation and task- or user-level benefits, few explore how organizations leverage the capacity freed by these technologies or how such changes influence strategic and operational adaptation—an area warranting deeper investigation [84], [85], [86]. Despite the widespread adoption of Microsoft 365 and Google Workspace, these platforms are notably absent from the current research sample. This is also true for articles addressing post-adoption dynamics, largely due to the novelty of GAI-enabled DATs [87]. Although our findings suggest positive effects, comprehensive empirical validation—particularly within large enterprise contexts and across industries—remains limited. To address these gaps, we suggest leveraging established IS theories [88]. The TAM can support research on individual adoption and sustained use. The technology–organization–environment (TOE) framework offers a holistic lens for analyzing organizational adoption conditions. For

post-adoption dynamics, dynamic capabilities theory can explain how firms reconfigure resources to generate long-term value, while adaptive structuration theory provides insight into how DATs shape and are shaped by evolving work practices. We recommend longitudinal and case-based methods to trace adoption trajectories and long-term impact, complemented by controlled experiments, expert interviews, and large-scale surveys [42], [47], [59]. Beyond performance metrics, articles should examine structural shifts—such as evolving roles, skills, and workforce distribution—and their implications for strategy and competitiveness. Fig. 5 outlines potential research questions across five key research streams, organized into two rows: the first focuses on motivations and considerations for adopting GAI-enabled DATs in proprietary productivity software; the second highlights organizational shifts resulting from their usage and adoption.

IX. Conclusion and Limitations

This SLR analyzed 61 articles on organizational support via DATs and their strategic implications. In response to RQ1, the review identified five primary areas of impact: productivity and efficiency enhancement, strategic business growth, resource optimization, quality improvement, and the promotion of creativity and learning. Regarding RQ2, the findings highlight a lack of research on long-term strategic adaptations, largely due to the novelty of GAI-enabled DATs. Addressing this gap is essential to advance scholarly understanding of effective DAT implementation.

Limitations of the paper at hand include exclusive reliance on IS journals indexed in Scopus, potentially overlooking interdisciplinary insights. Additionally, the frequency-based analytical methods and VOSviewer utilized in this study may introduce algorithmic biases and do not permit the establish-

	Research stream				
	Productivity & efficiency	**Business growth & development**	**Cost & resource optimization**	**Quality**	**Creativity & learning**
Key focus areas for organizations using GAI-enabled DATs in proprietary productivity software. (referred to as DAT for readability in this table)	• To what extent do DAT impact productivity and operational performance over a X-year period? • By how much do DAT reduce mental health sick leaves by alleviating high workloads? • How do proprietary DATs transform workplace productivity and efficiency? • What is the critical mass of adoption within companies required to realize productivity gains from Copilot? • What key tasks see the greatest efficiency improvements through DAT integration?	• How can DATs impact organizational expansion? • What measurable impact do DATs have on business cycle time reduction? • By how much does market capitalization increase through DAT implementation? • How do DATs qualitatively reshape strategic business growth and value creation processes? • What business areas demonstrate significant growth potential due to DAT deployment? • What new strategic directions can organizations pursue based on DAT capabilities?	• What are the cost savings achievable through DAT? • How does the implementation of DAT impact the average number of work hours saved per employee per week? • What specific business functions achieve the highest cost savings through DAT implementation? • What specific business functions achieve the highest cost savings through DAT implementation? • What resource allocation strategies are most effective when incorporating DAT-driven automation?	• How do DAT influence work/output quality (e.g. NPS, customer satisfaction)? • To what extent do DAT help reduce cull across different work processes? • What changes in quality and service delivery occur through DAT integration? • What quality assurance processes are most significantly improved through DAT integration? • What quality-related KPIs show measurable improvement due to DAT usage?	• How many additional non-native speakers are employed through DAT application and support? • What alterations in creative processes and learning methods are driven by DATs? • What creative processes/job benefit most from DAT support? • What competencies/skills are essential for maximizing the effectiveness of DAT usage? • What learning outcomes are most significantly enhanced by DAT integration?
Organizational shifts driven by GAI-enabled DATs in proprietary productivity software.	• How does overall business performance change after reallocated capacity is freed up? • What changes in workforce roles and team dynamics are driven by DATs? • What is the critical mass of adoption within companies required to realize productivity gains from Copilot? • How does DAT implementation affect workforce dynamics, job roles, and team performance?	• What impact can DAT have on organizational strategy, overall performance, and market perception? • What proportion of business growth can be attributed to improved operational efficiency from GAI-enabled DATs • What changes in organizational structure and governance are attributed to DAT implementation? • How do DAT reshape organizational strategies and business processes? • What new strategic directions can organizations pursue based on DAT capabilities?	• How effectively do organizations measure the financial impact of DAT-driven resource reallocation? • How do companies perceive and manage cost savings and resource reallocations? • What impacts occur from resource redistribution post-DAT implementation? • What resource allocation strategies are most effective when incorporating DAT-driven automation?	• How do organizations track quality improvements from DAT integration? • What adaptations occur in governance to maintain quality post-DAT implementation? • What quality assurance processes are most significantly improved through DAT integration? • What KPIs show measurable improvement due to DAT usage?	• How can organizations assess DAT-driven innovation outcomes? • How much additional innovation is driven by DAT implementation? • How do DATs influence creativity, learning processes, and innovation within organizations? • What creative processes benefit most from DAT support? • What learning outcomes are most significantly enhanced by DAT integration?

Fig. 5. Indicative potential research questions in DAT research

ment of causal relationships [41], [89]. Finally, the narrow search strategy could have resulted in biases toward specific terminologies or perspectives, thereby limiting the broader applicability of findings due to terminological ambiguities, commonly referred to as jingle-jangle fallacies, surrounding DAT [1]. Future articles should broaden their methodological scope to comprehensively capture interdisciplinary insights and mitigate these limitations.

APPENDIX

Additional data in form of an online appendix is provided here: https://doi.org/10.6084/m9.figshare.28776362.v1

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