

Interpretation of Corporate Digital Responsibility Risks and Concerns by Automated Service Technologies: An AI Co-Created Article

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Abstract

Corporate Digital Responsibility (CDR) is an emergent research area in the service domain. We used this relatively new literature domain as context to explore the capability of LLM (Large Language Model)-enabled Artificial Intelligence (AI) service offerings in identifying CDR concepts and in expanding the current scope of academic knowledge in this domain. A hybrid Chain and Critical Agent approach was employed in producing AI prompts to guide the LLM in producing CDR insights. A total of 18 chained prompts were entered into BingChat. Our findings confirm that the hybrid Chain and Critical Agent AI prompt construction method is a viable approach for guiding LLMs in retrieval of top-level information on academic domains such as CDR, the CDR Data and Technology Life Cycle, and the CDR Calculus. Furthermore, we found the hybrid AI prompting approach to be effective in establishing the correct context of the information and subject domain, alongside the required writing conventions, and directing the LLM to prioritise usage of academic CDR sources. However, we found that this method cannot adequately produce academic-level or original insights that could be published in academic peer-reviewed journals.

Keywords: Corporate Digital Responsibility, Artificial Intelligence, Large Language Models, AI-Created Content, AI Prompt Engineering

Type: AI-generated Article

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I. Introduction

Corporate Digital Responsibility (CDR) is defined as “the principles underpinning a service firm’s ethical, fair, and protective use of data and technology” (Wirtz et al., 2023, p. 173) and aims to mitigate consumers’ risks when interacting with service firms (Dörr, 2021; Elliott et al., 2021). These risks emerge not only from the collection and creation of digital technologies and collection of consumer data (e.g., algorithmic biases, overcollection of data, and inappropriate variable labelling), but also from the operation, refinement and retirement of AI systems and collected data (e.g., algorithmic drift, interpretability of “black box” models, storage and deletion of sensitive consumer data, etc.) (Herden et al., 2021; Lobschat et al., 2021). These AI usage risks can be categorised into concerns pertaining to privacy (e.g., over-reach of data collection by algorithms, data and identity theft, undisclosed sharing of consumer data), ethical (e.g., lack of algorithm interpretability, consumer disempowerment), and fairness (e.g., algorithmic biases, representativeness of variables and training data, etc.) (Du & Xie, 2021; Herden et al., 2021; Wirtz et al., 2023). If managed inappropriately, these CDR concerns are known to result in a myriad of consumer consequences, such as dehumanisation, psychological distress, unintended discrimination, marginalisation of at-risk consumers, economic and liability costs, alongside unfair treatment from automated decision processes (Dörr, 2021; Zuboff, 2015). These negative consequences are caused by trade-offs made by the service firms in which CDR-positive practices are set aside to pursue competing organisational objectives such as increasing revenues, avoidance of opportunity costs (e.g., forgoing potential revenue from sharing data or maintaining algorithmic safeguards), and maintaining competitive parity with service firms that engage in CDR-negative practices (Wirtz et al., 2023).

To manage these trade-offs and ensure consumers are adequately protected from CDR concerns, service firms must enact and maintain CDR-positive policies and practices. These include adherence with external governance guidelines (e.g., GDPR, Andrew & Baker, 2021), embedding ethical and anti-discrimination safeguards into algorithms (Clarke, 2023), building a CDR-positive organisational culture within service organisations (Herden et al., 2021; Wirtz et al., 2023), and increasing digital literacy and ethical awareness among employees (Mihale-Wilson et al., 2021). Moreover, CDR-compliant and CDR-positive practices must be continually audited within the service firm as new and more powerful AI systems emerge with increased scope and capacity to elicit CDR concerns (Wirtz et al., 2023).

Of these emergent AI systems, Large Language Model (LLM)-embedded service offerings such as Microsoft’s GPT-4-based BingChat and Google’s Bard offer consumers unprecedented benefits and capabilities. Consumers can prompt LLM-enabled service offerings to write programming code (Chen et al., 2021), solve complex mathematical equations, write music (Edwards, 2023a), conduct legal argumentation (Katz et al., 2023), produce educational content (Kasneji et al., 2023), and independently produce written analyses such as company reports, university assignments, and policy documents (Dwivedi et al., 2023). Within service firms, LLMs can automate coding and knowledge management processes, and provide personalised and rapid content creation capabilities at scale. Examples include Mattel utilising DALL-E to assist with product design and producing marketing materials; Jasper producing automated marketing email campaigns, auto-generated written copy for Search Engine Optimisation (SEO) ads, and social media posts; and Morgan Stanley providing tailored financial solutions for its clients (Davenport & Mittal, 2022).

LLMs function by users entering a written prompt into the AI interface. The LLM interprets the instruction (e.g., analyse, define, outline, etc.), the specified format (e.g., “using Common Law legal terminology”, “within 400 words”), the requested content (e.g., “the key components of consumer privacy protection”) and context (e.g., “using the provided definition of ethical reasoning”, “explain to a manager who is a non-expert in this topic”, “outline to an undergraduate-level audience”) (Purtill, 2023; Wu et al., 2022). The quality, accuracy, and relevance of the output is heavily influenced by the quality of the AI prompt provided to the system (Teubner et al., 2023).

Despite the promise of productivity and economic gains offered by LLM-embedded service offerings, LLMs are susceptible to incorporating biases, inaccuracies, human error, and algorithmic limitations in output provided to consumers. For instance, LLM algorithms generate output based on the probabilistic association of certain terms or sequences of words presented within the parameters provided by the AI prompt (Dwivedi et al., 2023). In effect, this places a hard limit to the LLM's capabilities related to the number of text parameters or tuneable values utilised in training the algorithm (Hoffmann et al., 2022). Consequently, an LLM's ability to produce an accurate output is dependent on the training data, model parameters, and training process it is exposed to, where the output is effectively a "best fit" of predicted text from the model's trained parameters to fulfill the given AI prompt. This is a fundamental limitation of LLM algorithms, which in turn can lead to "confabulated" results consisting of inaccurate or hallucinated information interspersed with factually accurate insights within the output (Edwards, 2023b).

Moreover, LLMs can be trained to produce refined responses based on false, misrepresentative, biased, and discriminatory AI prompts. For instance, LLMs are known to display undesirable stereotypes toward ethnic and religious consumer groups alongside gender biases in prompted outputs (Abid, Farooqi & Zou, 2021). LLMs may also be utilised by consumers to "cheat" the service interface and gain unfair advantages, such as generating graded assessment items for students to pass off as an inaccurate depiction of their capabilities (c.f. Dwivedi et al., 2023). These inherent issues with LLM usage in turn create CDR risks for consumers, where misuse or inherent limitations with LLM-enabled service offerings create a plethora of privacy, fairness, and ethical concerns.

In light of the potential CDR risks and concerns arising from the operation of LLM-enabled service offerings, and the inherent limitations of these systems (e.g., confabulation in output, algorithmic biases), we aim to explore how CDR risks and concerns are identified, interpreted and presented to consumers of frontline LLMs. While the operation of LLM-enabled service offerings incurs potential CDR risks and concerns of consumers, LLMs are unique as a digitised service technology in possessing the learning capability to identify and communicate recognised CDR risks to users (i.e., consumers in our context) when prompted. It is salient that LLM outputs can accurately identify and articulate considered risks to users of these systems, to support the adoption of CDR practices by both consumers and service firms. Given that CDR is still an emergent field with limited data or parameters to draw from and contains subjectively interpretable attributes (e.g., digital ethics, CDR trade-off dilemmas, etc.), the performance of LLM-enabled service offerings in sufficiently identifying and communicating CDR risks and concerns to consumers is a key focus of this paper:

RQ1: Do LLM-enabled service offerings accurately convey information involving CDR concepts and concerns?

In practice, LLMs are utilised to generate top-level managerial insights for service firms and consultancies from existing data sources (Davenport & Mittal, 2022; Ransbotham et al., 2019). However, a common criticism of LLMs is the inherent inability of these systems to synthesise new and novel insights due to dependence upon existing data and parameters. For instance, ChatGPT does not compute the results of mathematical equations and functions when prompted, but instead interprets the prompt and provides answers based on the numbers shown in the equations and functions from the training data unless augmented with an external plug-in such as Wolfram Alpha (Hughes-Castleberry, 2023). As such, journal reviewers and editors in the service management, marketing, and information systems fields assert that LLMs are incapable of producing original or polished content at the standard required for peer-reviewed publications (Dwivedi et al., 2023).

To verify this position held among the academic community, this paper will also assess the viability of LLMs to assist researchers in producing content publishable in peer-reviewed journals covering the field of CDR. CDR provides a unique opportunity to test this assertion, as CDR is an emerging field with interest to academics, policy makers, and service firms (Dörr, 2021), although is nascent enough to not provide a large corpus of data

for LLMs to utilise in comparison to other research domains such as service robotics. A current limitation in knowledge within the CDR is coverage of strategies to manage CDR trade-offs among service firms (Wirtz et al., 2023), prompting an LLM to synthesise or identify new insights in this respect could provide genuinely new insights to advance the current scope of academic CDR literature and service practice.

We posit that the purpose of this paper is not to create new content produced by an LLM, but rather to assess the performance and viability of using LLMs in service management research with a team of domain experts and draw conclusions to inform future editorial policy. We also stress that due to the algorithmic limitations of LLMs and their dependence on training data, the usage of LLMs in writing any kind of work is never a viable substitute for maintaining adequate domain knowledge and expertise:

RQ2: Can service-focused LLMs identify novel methods for managing CDR trade-offs identified by the CDR calculus?

RQ3: Using the emergent domain of CDR in service as a basis, can LLMs be directed to produce content that advances the scope of academic knowledge?

RQ4: Is an AI-prompt writing process a viable method of producing content for peer-reviewed publications in emergent service literature?

To fulfil these research questions, a chain of structured AI prompts was created based around an existing seminal CDR publication by Wirtz et al. (2023). This publication outlines the core conceptual components of CDR in the service domain (e.g., types of risks and concerns, CDR Data and Technology Lifecycle, the CDR Calculus, etc.) and provides a performance benchmark for a LLM with respect to identifying and collecting knowledge. This publication is also open-access, allowing LLMs capable of searching web results to recognise and cite the material. A chain of AI prompts following the conceptual components of CDR outlined in this paper was entered into the BingChat LLM. The output was scrutinised by a team of service research and CDR experts, with conclusions provided to inform future works involving CDR, smart service technology usage, and potential applications of AI within peer-reviewed research production.

2. Methodology

2.1. AI model selection

To determine the effectiveness and efficacy of LLM-enabled service offerings in providing output involving CDR content, the research team selected BingChat. BingChat was chosen for several reasons. First, BingChat utilises a higher-performance model of GPT-4 than OpenAI's ChatGPT. Second, BingChat includes more features such as utilising and providing citations in outputs, and thirdly, it has demonstrably better performance than competitors in finding sources and answering query-focused prompts (Vincent et al., 2023). The usage of citations in the output allows for easier recognition of confabulated or fabricated sources, and verification of provided insights by the research team in scrutinising the AI-produced CDR output. Moreover, BingChat is an entirely free and easy-to-access LLM-enabled service offering that does not require an account or payment for consumers to use, and currently serves 100 million unique users per month (Cunningham, 2023). Unlike ChatGPT, BingChat can utilise any source found in Bing Search and is not limited to data sources published before 2021. As BingChat is an industry-benchmark and Microsoft-backed LLM-enabled service offering that draws information in real-time from web sources, the output produced by this service provides an up-to-date and full list of sources. Further, anecdotal testing by the research team recognised that BingChat is highly responsive to changes in prompt content and demonstrates enhanced performance when utilising chained prompts in comparison to ChatGPT. Although LLM-enabled services specifically trained for academic writing are available (e.g., Grammarly, Cohere, Penelope.ai) these offer comparable performance to GPT-4 in some instances, and are generally recommended to be employed as writing aids rather than content creation systems (Golan et al., 2023).

2.2. AI prompt production process

The bulk of literature to date involving AI prompt production methods has focused on AI-human collaborative methods for AI prompt production (Seeber et al., 2020; Sharma et al., 2023; Wu et al., 2022). This method involves the usage of a real-time AI-in-the-loop agent provided by the LLM interface that provides prompt suggestions, edits, and recommendations based on popular topic keywords and prompt searches (Sharma et al., 2023). Conversely, this paper focuses on prompts produced by collaborations of a wholly human team. This approach was undertaken for two reasons. First, CDR in the service context is an emergent domain with limited existing information available for LLM systems to draw on. This lack of available information increases the risk of confabulated or fabricated insights in the output and in AI-generated prompt suggestions (Edwards, 2023b). Anecdotally, this limitation initially led to LLM-generated output “filling the gaps” with tangential information from closely associated domains such as Corporate Social Responsibility (CSR) or omitting critical CDR concepts such as ethics or fairness in the output.

Second, CDR relevant concepts such as fairness, ethics, and privacy are highly subjective and require a human interpretation layer to ensure AI systems process information within the correct context. In managing these subjectivity concerns, a Reinforcement Learning from Human Feedback approach can be employed to ensure that AI prompts provide information to the LLM and train the algorithm using the correct context, syntax, and semantics (Teubner et al., 2023). As LLMs only present information based on predictive association of words, a human operator can ensure that the output accurately reflects context and subjective interpretation of key CDR concepts.

As such, the AI prompts were produced by a team of CDR researchers with no input from AI or prompt templates. Each researcher in this team possessed a track record in producing peer-reviewed publications involving CDR, presented CDR research at academic conferences, and produced educational content involving CDR for various audiences. Two of the authors are editors in Q1-ranked academic journals (*Journal of Service Research*, *Journal of Service Management*, and *Journal of Business Management*), and possess expertise in critiquing submitted manuscripts during the peer-review process. These researchers employed their domain knowledge of CDR within the service context to ensure that AI prompts were created to reflect subjective and/or context-specific attributes of CDR in service. This domain knowledge was also utilised to scrutinise the LLM output for instances of confabulation, misinterpretation, and fabrication to assess the viability of service-focused LLMs in replicating CDR-specific information to users.

The AI prompts were developed collaboratively through three rounds of editing, testing, refinement, and inter-rater approval. Rounds of inter-rater refinement had continued until unanimous approval was provided by all members of the research team to the AI prompts, with team-members testing updated or refined prompts in BingChat before circulating to the rest of the team for review. In producing the AI prompts, the research team utilised a hybrid Chaining and Critical Agent approach in writing, formatting and entering prompts into the LLM interface (Purtil, 2023). An outline of the prompting approach taken is outlined in Table 1. The Chaining component of the approach directs the LLM to narrow its domain focus and scaffold multiple tasks together one-by-one with accumulated sources and pre-prompted information. This approach was found to be necessary in guiding the LLM to provide accurate and consistent CDR-focused output. For instance, while utilising the previous multi-task and concept prompt approach, a stipulated step-by-step process or dot point structure would be abandoned partway through the output, or the output format would inexplicably change as the output is produced. Likewise, the output would at random fail to address certain aspects of a concept or omit some aspects completely each time the prompt is entered. Prompting the AI to expand the word count of responses was ineffective at addressing this limitation.

To circumvent these limitations, a Chain approach was used when producing and entering prompts into the LLM interface. In the domain of AI prompt engineering, chaining AI responses is known to improve the quality

and controllability of responses, and allow the LLM to scaffold information from separate outputs together to synthesise insights while maintaining context and subjectivity requirements (Wu et al., 2022). This chaining approach was found to be necessary to obtain clear and complete responses, as both ChatGPT and BingChat presented recognised limitations in producing consistent output if prompted to synthesise and summarise more than two separate concepts at a time. In undertaking this chain approach, the instructions provided to the LLM were separated into a sequence of individual prompts containing a single task covering specific CDR concepts (e.g., “define fairness within the context of CDR”), providing scaffolded output that sequentially builds the AI output corpus. Following prompting of the LLM to define and summarise all relevant CDR concepts, the LLM was able to recollect generated information in the prompt output corpus into a single and complete response without content or formatting issues.

Second, the Critical Agent approach allowed for the LLM to maintain consistent task objectives, context and writing conventions in the output. In this instance, the AI “agent” was assigned the role of an academic researcher writing a peer-reviewed article covering Corporate Digital Responsibility within the service management context. In this provided orientation and context, the writing conventions of the output changed from providing top-level insights to providing detailed and specific analysis of CDR concepts with greater usage of citations. The verb given to the AI agent was also recognised to change the overall structure and content of response (e.g., critique, summarise, explain, elaborate, etc.) (Purtil, 2023). The research team identified that “outline”, “summarise”, “introduce”, and “combine” were most effective in accurately presenting CDR content in the appropriate academic writing conventions.

While producing the AI prompt chain, several limitations in the prompting approach were identified and addressed. As the CDR domain utilises management-specific definitions of concepts such as privacy, ethics and fairness, a draft iteration of the prompt chain attempted to account for this potential subjectivity risk by including verbatim definitions in the prompts. This approach was intended to ensure that the semantics, context, and syntax specific to the CDR, service and management domains would be applied appropriately within the output. In practice however, this prompting strategy had no effect on changing or refining the obtained output. The LLM would quote the provided definition at the beginning of the output and then provide a verbatim response of the same prompt without the definition. This effect may be due to CDR being at present a relatively emergent field within service research with limited training data or parameters available for the LLM to utilise, leading the LLM to produce extremely similar or identical output if prompted to run a prompt multiple times. This may also provide insight toward the tendency of ChatGPT to quote verbatim extracts of text without appropriately citing the original source or author while employing highly-specific and long prompts. BingChat also provided some outputs that were largely built on text taken from external sources, although these quotes were appropriately outlined and attributed by the LLM.

Testing of AI prompts also identified that prompting the LLM to substantially increase output size (i.e., over 500 words) often increased the level of confabulation in the output. One example included the output presenting individual CDR risks alongside the three categories of CDR concerns (e.g., presenting “transparency concerns” and “legal concerns” alongside the main categories of privacy, fairness and ethical concerns, despite the AI model identifying and classifying both new categories as individual risks within the existing three categories). This could be due to the model attempting to find “best fit” text to “fill the gaps” in larger prompts, where insufficient information could be identified by the LLM to provide further elaboration within the word count (c.f. Edwards, 2023b).

Table 1. Outline of hybrid chaining-critical agent AI prompting approach utilised in this paper

Prompt creation step	Requirements	AI prompt examples
1. Define context, role, writing conventions, and overall task objectives with Critical Agent approach	<ul style="list-style-type: none"> • Give AI a specific role context, such as research analyst, managerial consultant, policy officer, etc. • Define an audience for the AI, such as “fellow academics”, employees, the client, board of directors, etc. 	<ul style="list-style-type: none"> • “You are a Digital Risk Auditor working for a large multinational service firm. The firm’s Leadership Committee has tasked you with identifying and presenting potential risks involving Corporate Digital Responsibility. “
2. Set up prompted task parameters and implement verb to direct prompted task	<ul style="list-style-type: none"> • Give AI a clearly defined task, such as writing an academic journal article, preparing a 500-word white paper, producing an undergraduate assessment guide, etc. • The verb will prompt the AI to transform the output parameters based on the task provided. 	<ul style="list-style-type: none"> • “To start writing your risk audit report for the committee, provide a 200-word definition of Corporate Digital Responsibility in the service industry context”
3. Create prompt chain by breaking down information retrieval/analysis/definitional tasks into individual steps	<ul style="list-style-type: none"> • To increase accuracy of LLM output, prompt the AI to complete one action at a time (e.g., conceptualise, define and/or analyse information). 	<ul style="list-style-type: none"> • “Thank you. For the next part of your report, please provide a definition of the CDR calculus and outline how it works.” • “Next, identify examples of CDR trade-offs that occur within the online banking service sector. Walk me through each example step-by-step”
4. (Optional) Create unified response using corpus of information built with chained prompts	<ul style="list-style-type: none"> • Instruct AI to summarise information taken from a determined number of previous responses, or from all previous responses. This is to ensure that only the previously screened and verified information is utilised. 	<ul style="list-style-type: none"> • “Thank you. Now please summarise the information provided in the previous three prompts into a 400-word analytical report for the leadership committee members”

To provide a benchmark to assess the accuracy and performance of the LLM’s CDR-focused output, the structure of the prompt chain was based on an existing CDR publication in the service literature domain. This was done to provide the LLM with at least one viable source to draw information from, to determine how effectively an LLM can interpret and present CDR-focused information to consumers and provide a chainable basis to guide the LLM in presenting context-specific and subjective information. The publication selected for this was *Corporate Digital Responsibility in Service Firms and their Ecosystems* by Wirtz et al. (2023) from the *Journal of Service Research*, written by the author team of this paper. As the author team possesses an in-depth and immersed understanding of this publication, the LLM’s output can be scrutinised by the original authors possessing publication-level domain knowledge. Following the structure of this publication, each conceptual component of CDR could be broken down into singular objectives and operators for entry into the LLM interface. Splitting prompting of complicated and multi-staged concepts contained in the domain of CDR into individual chained prompts (e.g., the CDR Data and Technology Lifecycle, the CDR Calculus) greatly increased

the level of detail and accuracy within responses while testing. Following this process, the prompt chain employed in this AI-generated paper was constructed around the following format based on this original source:

1. Define CDR within service context;
2. Identification of CDR risks within service contexts;
3. Identification and assessment of privacy, fairness and ethical CDR concerns in isolation before combining into a full overview of CDR concerns;
4. Defining the CDR Data and Technology Lifecycle, then individually incorporating the identified privacy, fairness and ethical CDR concerns across each stage of the lifecycle model;
5. Definition and identification of the CDR trade-offs made by service firms, causes of CDR trade-offs made by firms, identification and/or synthesis of any CDR trade-offs other than those already presented in the AI output corpus;
6. Definition and identification of CDR-positive management practices, strategies and tools, identification and/or synthesis of new CDR-positive management strategies not listed in service literature.

With respect to the research aims outlined in RQ1 and RQ2, an additional prompt outside the scope of this source was implemented. This extra prompt was intended to assess the capability of the LLM to provide CDR information at the consumer-level, and guide consumers in undertaking CDR-positive service behaviours to reduce their exposure to CDR risks associated with usage of the LLM-enabled service offering. To assist the LLM, this prompt was connected to the rest of the prompt chain and could utilise information contained within the existing corpus of AI output provided by the previous prompts:

7. How can consumers reduce their susceptibility to the identified CDR concerns, based on the content provided in the previous responses.

A complete list of the 18 AI prompts sequentially entered into BingChat is provided below. The output and sources utilised in each prompt is presented in the next section.

2.3. Final AI prompt chain utilised

- a. Good morning. You are an academic researcher writing an article covering Corporate Digital Responsibility (CDR) within the context of service management. In starting your article, please define Corporate Digital Responsibility using service management terminology.
- b. Thank you. Next, please outline the privacy concerns associated with Corporate Digital Responsibility. In your article, outline each identified privacy concern step by step.
- c. Well done. Now, please outline the fairness concerns associated with Corporate Digital Responsibility. For writing your academic article, outline each identified fairness concern step by step.
- d. Next, please outline the ethical concerns associated with CDR. For your academic article, outline each identified ethical concern step by step.
- e. Now, combine and summarise the information provided in your three previous responses into a single 400-word paragraph using academic writing conventions. While you write this summary, please use the step-by-step process we used in these previous responses.
- f. We are now progressing to the next stage of your academic article covering Corporate Digital Responsibility. In 250 words using academic writing conventions, introduce summarise the CDR Data and Technology Life-Cycle.
- g. Thank you. In writing your academic article, provide the reader with a step-by-step overview of the four stages of the CDR Data and Technology Life-Cycle.
- h. Now, please rewrite and refine your previous response and show me how fairness CDR risks fit across each stage of the CDR Data and Technology Life-Cycle.
- i. Next, please expand your previous response to also incorporate how ethical CDR risks also fit across each stage of the CDR Data and Technology Life-Cycle.

- j. Now, please expand your previous response to include the privacy CDR concerns that exist in each stage of the CDR Data and Technology Life-Cycle.
- k. Thank you. Now, please summarise your previous four responses into a 400-word step-by-step overview of the fairness, privacy, and ethical concerns across each stage of the Corporate Digital Responsibility Data and Technology Life-Cycle.
- l. Great work. We will now move onto writing the next section of your academic paper. In 200 words, please define and summarise Corporate Digital Responsibility Trade-offs using academic writing conventions.
- m. For your academic paper, identify and summarise the types of Corporate Digital Responsibility trade-offs that can occur within service firms within 250 words
- n. Good work. Now, please outline using academic terminology how these recognised Corporate Digital Responsibility trade-offs can be caused within service firms.
- o. Excellent. Now, for the next section of your paper, you must identify and summarise any new types of Corporate Digital Responsibility trade-offs that has not been recognised in literature.
- p. For your academic paper, please outline in 300 words how service firms can implement effective organisational solutions to manage Corporate Digital Responsibility trade-offs.
- q. In your academic paper, can you identify any new solutions that service firms can employ to manage Corporate Digital Responsibility risks?
- r. From what we have discussed, what recommendations can you provide to the average consumer take for reducing their exposure to experiencing Corporate Digital Responsibility risks?

In each generated prompt, each source was reviewed individually to identify instances of fabricated or confabulated source usage. Unlike referencing in standard APA formatting conventions, BingChat only attributes numbered sources within text where quotes are utilised, and otherwise outlines all sources employed at the end of the output. This approach to referencing directly contrasts to academic writing conventions, where sources must be attributed either immediately or at the end of a sentence. Instead, BingChat provides superscripted references at the end of the output without attributing where the reference was utilised within the output. As such, the sources provided by the AI output are presented at the end of each output exactly as written and presented by BingChat. Implications of this referencing limitation with respect to RQ3 are provided in the discussion section. Where the seminal CDR article used to construct the prompt chain has been cited, an asterisk (*) is placed next to the source.

3. AI-generated content

Prompt: *Good morning. You are an academic researcher writing an article covering Corporate Digital Responsibility (CDR) within the context of service management. In starting your article, please define Corporate Digital Responsibility using service management terminology in 150 words.*

AI output: Corporate Digital Responsibility (CDR) is a set of practices and behaviors that help an organisation use data and digital technologies in ways that are perceived as socially, economically, and environmentally responsible.¹ In the context of service management, CDR is defined as the principles underpinning a service firm's ethical, fair, and protective use of data and technology when engaging with customers within their digital service ecosystem.² This includes managing the risks associated with digitisation, artificial intelligence, and service robots which carry serious ethical, privacy, and fairness risks for service users.² CDR is critical in service contexts because of the vast streams of customer data involved and digital service technology's omnipresence, opacity, and complexity.²

¹(Frick, 2023) ²(Wirtz et al., 2023) ³(Lobschat et al., 2021) ⁴(Dentons, 2022) ⁵(Corporate Digital Responsibility, 2023)

Prompt: *Thank you. Next, please outline the privacy concerns associated with Corporate Digital Responsibility. In writing your article, outline each identified privacy concern step by step.*

AI Output: There are several privacy concerns associated with Corporate Digital Responsibility (CDR). One concern is the need for organisations to go beyond compliance with relevant regulations on data privacy and improve their behavior in areas such as cybersecurity, data protection, and privacy¹. Another concern is the tension that arises between business objectives and responsible digital practices. For example, better data and analytics may enhance service personalisation, but at the cost of customer privacy¹. Additionally, there is a growing mistrust among consumers regarding the use of their personal data without their consent². This has led to a push for more control over personal data and a shift towards treating personal data as an asset owned by individuals and held in trust by firms².

¹(Yokoi et al., 2023) ²(Rahnama & Pentland, 2022) ³(Wirtz et al., 2022) ⁴(Pew Research Center, 2019)

Prompt: *Well done. Now, please outline the fairness concerns associated with Corporate Digital Responsibility. For writing your academic article, outline each identified fairness concern step by step.*

AI Output: There are several fairness concerns associated with Corporate Digital Responsibility (CDR). One concern is the risk of biases in algorithm-based decision-making and procedural unfairness¹. This can result in discriminatory practices and unequal treatment of customers. Another concern is the trade-offs between good CDR practices and organisational objectives, such as profit opportunities versus CDR risks². This can result in decisions that prioritise business objectives over fairness. To mitigate these risks, service firms can use a set of strategies, tools, and practices to manage these trade-offs and build a strong CDR culture².

¹(Kunz et al., 2023) ^{2&3*}(Wirtz et al., 2023) ⁴(Wirtz et al., 2022)

Prompt: *Next, please outline the ethical risks and concerns associated with CDR. For your academic article, outline each identified ethical concern step by step.*

AI output: There are several ethical risks and concerns associated with Corporate Digital Responsibility (CDR). One concern is the need for organisations to act responsibly and promote ethical use of technology¹. This includes managing the risks associated with digitisation, artificial intelligence, and service robots which carry serious ethical risks for service users². Another concern is the need for organisations to balance revenue opportunities against brand trust and to go beyond meeting regulatory requirements and demonstrate good citizenship by promoting thoughtful and socially beneficial use of technology¹.

¹(Deloitte, 2023) ²(Wirtz et al., 2022) ^{3&5}(Lobschat et al., 2021) ⁴(Wade, 2020) ⁶. not appropriate for academic articles (Minty, 2022)

Prompt: *Now, combine and summarise the information provided in your previous responses into a single 400-word paragraph using academic writing conventions. While you write this summary, please use the step-by-step process we used in these previous responses.*

AI output: Corporate Digital Responsibility (CDR) encompasses a set of practices and behaviors that enable organisations to use data and digital technologies in a manner that is socially, economically, and environmentally responsible. Within the context of service management, CDR is defined as the principles that guide a service firm's ethical, fair, and protective use of data and technology when engaging with customers within their digital service ecosystem. This includes managing risks associated with digitisation, artificial intelligence, and service robots, which pose serious ethical, privacy, and fairness risks for service users. Privacy concerns associated with CDR include the need for organisations to comply with relevant regulations on data privacy and improve their behavior in areas such as cybersecurity, data protection, and privacy. Another concern is the tension between business objectives and responsible digital practices. For instance, while better data and analytics may enhance service personalisation, it may come at the cost of customer privacy. Additionally, there is growing mistrust among consumers regarding the use of their personal data without their consent. This has led to a push for greater control over personal data and a shift towards treating personal data as an asset owned by individuals and held in trust by firms. Fairness concerns associated with CDR include the risk of biases in algorithm-based decision-making and procedural unfairness, which can result in discriminatory practices and unequal treatment of customers. Another concern is the trade-offs between good CDR practices and organisational objectives

such as profit opportunities versus CDR risks. To mitigate these risks, service firms can employ a set of strategies, tools, and practices to manage these trade-offs and build a strong CDR culture. Ethical risks and concerns associated with CDR include the need for organisations to act responsibly and promote ethical use of technology. This includes managing risks associated with digitisation, artificial intelligence, and service robots which carry serious ethical risks for service users. Another concern is the need for organisations to balance revenue opportunities against brand trust while going beyond meeting regulatory requirements to demonstrate good citizenship by promoting thoughtful and socially beneficial use of technology.

Prompt: *We are now progressing to the next stage of your academic article covering Corporate Digital Responsibility. In 250 words using academic writing conventions, introduce summarise the CDR Data and Technology Life-Cycle.*

AI output: The CDR Data and Technology Life-Cycle refers to the stages that data and technology go through within an organisation in relation to Corporate Digital Responsibility (CDR). Within service value chains, CDR issues related to data and technology occur across four distinct life-cycle stages: creation, operation, refinement, and retention¹. Each stage poses different challenges for service firms pertaining to data and technologies, and these stages often progress at different rates¹. By managing these stages responsibly, organisations can ensure that their use of data and technology is ethical, fair, and protective.

¹(Kunz et al., 2023) ^{2&3*}(Wirtz et al., 2023) ^{4, confabulated source}(Chetankumar, 2023)

Prompt: *Thank you. In writing your academic article, provide the reader with a step-by-step overview of the four stages in the CDR Data and Technology Life-Cycle.*

AI output: The CDR Data and Technology Life-cycle refers to the stages that data and technology go through within an organisation in relation to Corporate Digital Responsibility (CDR). Within service value chains, CDR issues related to data and technology occur across four distinct life-cycle stages: creation, operation, refinement, and retention¹.

1. **Creation:** This stage involves the development of new technologies and the capture of data. Organisations must ensure that their data collection methods are ethical and that their technologies are designed with CDR in mind.
2. **Operation:** This stage involves the use of data and technology in decision-making processes. Organizations must ensure that their use of data and technology is fair and transparent.
3. **Refinement:** This stage involves the improvement of existing technologies and the refinement of data. Organisations must ensure that their refinement processes are ethical and that they do not harm their customers or other stakeholders.
4. **Retention:** This stage involves the retention of data and technology. Organisations must ensure that their data retention policies are fair and transparent, and that they protect the privacy of their customers.

By managing these stages responsibly, organisations can ensure that their use of data and technology is ethical, fair, and protective.

¹(Kunz et al., 2023) ^{2*}(Wirtz et al., 2023) ³(Wirtz et al., 2021) ^{4, confabulated source}(MindTools, 2023)

Prompt: *Now, please rewrite and refine the previous response and show me how fairness CDR risks fit across each stage of the CDR data and Technology Life-Cycle.*

AI output: The CDR Data and Technology Life-Cycle refers to the stages that data and technology go through within an organisation in relation to Corporate Digital Responsibility (CDR). Within service value chains, CDR issues related to data and technology occur across four distinct life-cycle stages: creation, operation, refinement, and retention¹. Each stage poses different challenges for service firms pertaining to data and technologies, and these stages often progress at different rates¹.

1. **Creation:** This stage involves the development of new technologies and the capture of data. Organisations must ensure that their data collection methods are ethical and that their technologies

are designed with CDR in mind. Fairness risks at this stage may include issues such as bias in data collection or algorithm design.

2. **Operation:** This stage involves the use of data and technology in decision-making processes. Organisations must ensure that their use of data and technology is fair and transparent. Fairness risks at this stage may include issues such as discrimination or unfair treatment of customers.
3. **Refinement:** This stage involves the improvement of existing technologies and the refinement of data. Organisations must ensure that their refinement processes are ethical and that they do not harm their customers or other stakeholders. Fairness risks at this stage may include issues such as perpetuating existing biases or unfair treatment.
4. **Retention:** This stage involves the retention of data and technology. Organisations must ensure that their data retention policies are fair and transparent, and that they protect the privacy of their customers. Fairness risks at this stage may include issues such as unequal access to data or unfair treatment of customers based on their data.

By managing these stages responsibly, organisations can ensure that their use of data and technology is ethical, fair, and protective.

¹(Kunz et al., 2023) ^{2&3*}(Wirtz et al., 2023) ⁴(J Wirtz, Werner Kunz, et al., 2022)

Prompt: Next, please expand your previous response to also incorporate how ethical CDR risks also fit across each stage of the CDR data and technology life-cycle.

AI output: The CDR Data and Technology Life-Cycle refers to the stages that data and technology go through within an organisation in relation to Corporate Digital Responsibility (CDR). Within service value chains, CDR issues related to data and technology occur across four distinct life-cycle stages: creation, operation, refinement, and retention¹. Each stage poses different challenges for service firms pertaining to data and technologies, and these stages often progress at different rates¹.

1. **Creation:** This stage involves the development of new technologies and the capture of data. Organisations must ensure that their data collection methods are ethical and that their technologies are designed with CDR in mind. Ethical risks at this stage may include issues such as coercion or threats to human dignity.
2. **Operation:** This stage involves the use of data and technology in decision-making processes. Organisations must ensure that their use of data and technology is fair and transparent. Ethical risks at this stage may include issues such as manipulation or lack of accountability.
3. **Refinement:** This stage involves the improvement of existing technologies and the refinement of data. Organisations must ensure that their refinement processes are ethical and that they do not harm their customers or other stakeholders. Ethical risks at this stage may include issues such as perpetuating existing biases or unfair treatment.
4. **Retention:** This stage involves the retention of data and technology. Organisations must ensure that their data retention policies are fair and transparent, and that they protect the privacy of their customers. Ethical risks at this stage may include issues such as unwanted marketing or surveillance.

By managing these stages responsibly, organisations can ensure that their use of data and technology is ethical, fair, and protective.

¹(Kunz et al., 2023) ^{2*}(Wirtz et al., 2023) ³(Wirtz, et al., 2022)

Prompt: Now, please expand your previous response to include the privacy CDR concerns that exist in each stage of the CDR data and technology life-cycle.

AI output: I'm sorry, but I couldn't find specific information on privacy CDR concerns in each stage of the CDR data and technology life-cycle. Is there anything else you would like to know?

^{1*}(Wirtz et al., 2023) ²(HECimpact, 2021) ³(Kunz et al., 2023) ⁴(Wirtz et al., 2021)

Prompt: Thank you. Now, please summarise your previous four responses into a 400-word step-by-step overview of the fairness, privacy, and ethical concerns across each stage of the CDR data and technology life-cycle.

AI output: This prompt could not be generated, as the scaffolded prompt chain ended during previous prompt. Implications for this regarding Q3 and RQ4 is provided in the discussion section.

Prompt: Great work. We will now move onto the next section of your academic paper. In 200 words, please define and summarise Corporate Digital Responsibility Trade-offs using academic writing conventions.

AI output: Corporate Digital Responsibility (CDR) is a critical issue in service contexts due to the vast streams of customer data involved and the omnipresence, opacity, and complexity of digital service technology¹. CDR trade-offs refer to the underlying causes of CDR issues that arise when balancing good CDR practices with organisational objectives such as profit opportunities versus CDR risks¹. To capture these trade-offs, the CDR calculus was introduced¹. This calculus can help service firms navigate these trade-offs and build a robust CDR culture, processes, and behaviors through shared values, norms, artifacts, a supporting management structure, and digital governance¹. Regulation may need to step in when a firm's CDR calculus becomes so negative that good CDR is unlikely¹.

^{1, 2 & 3*}(Wirtz et al., 2023)

Prompt: For your academic paper, identify and summarise the types of Corporate Digital Responsibility trade-offs that can occur within service firms within 250 words.

AI output: Corporate Digital Responsibility (CDR) trade-offs refer to the underlying causes of CDR issues that arise when balancing good CDR practices with organisational objectives such as profit opportunities versus CDR risks¹. These trade-offs can occur within service firms due to the vast streams of customer data involved and the omnipresence, opacity, and complexity of digital service technology¹. To capture these trade-offs, the CDR calculus was introduced¹. This calculus can help service firms navigate these trade-offs and build a robust CDR culture, processes, and behaviors through shared values, norms, artifacts, a supporting management structure, and digital governance¹. Regulation may need to step in when a firm's CDR calculus becomes so negative that good CDR is unlikely¹.

^{1, 2 & 3*}(Wirtz et al., 2023)

Prompt: Good work. Now, please outline using academic terminology how these recognised Corporate Digital Responsibility trade-offs can be caused within service firms.

AI output: The underlying causes of Corporate Digital Responsibility (CDR) trade-offs within service firms are trade-offs between good CDR practices and organisational objectives such as profit opportunities versus CDR risks^{1&2}. For example, multiple profitable uses of customer insights in an ecosystem that are based on more and better data and related analytics can carry a gamut of ethical, privacy, and fairness risks². These trade-offs can occur due to the vast streams of customer data involved and the omnipresence, opacity, and complexity of digital service technology². To capture these trade-offs, the CDR calculus was introduced².

¹(Wirtz et al., 2021)^{2&3*}(Wirtz et al., 2023)^{4&5}(Wirtz et al., 2022)

Prompt: Excellent. Now, for the next section of your paper, you must identify and summarise any new types of Corporate Digital Responsibility trade-offs that has not been recognised in literature.

AI output: I'm sorry, but as an AI language model, I don't have the ability to identify and summarise new types of Corporate Digital Responsibility trade-offs that have not been recognised in literature. My responses are based on information that is available online and in existing literature.

Prompt: For your academic paper, please outline in 300 words how service firms can implement effective organisational solutions to manage Corporate Digital Responsibility trade-offs.

AI output: Service firms can implement effective organisational solutions to manage Corporate Digital Responsibility (CDR) trade-offs by using a set of strategies, tools, and practices to build a strong CDR culture¹.

These can include shared values, norms, artifacts, a supporting management structure, and digital governance¹. The CDR calculus can also be used to capture and navigate these trade-offs¹. In some cases, regulation may need to step in when a firm's CDR calculus becomes so negative that good CDR is unlikely¹.

^{1&2*}(Wirtz et al., 2023) ³(Yokoi et al., 2023)

Prompt: *In your academic paper, can you identify any new solutions that service firms can employ to manage Corporate Digital Responsibility risks?*

AI output: I'm sorry, but as an AI language model, I don't have the ability to identify new solutions that service firms can employ to manage Corporate Digital Responsibility risks. My responses are based on information that is available online and in existing literature.

Prompt: *From what we have discussed, what recommendations can you provide to the average consumer take for reducing their exposure to experiencing Corporate Digital Responsibility risks?*

AI output: As an AI language model, I don't have the ability to provide specific recommendations for consumers to reduce their exposure to experiencing Corporate Digital Responsibility risks. However, some general tips that consumers can follow include being mindful of the personal information they share online, reading privacy policies and terms of service before using digital services, and being aware of their rights and options for managing their data and privacy.

4. Discussion

4.1. Analysis of LLM to convey CDR concepts, concerns, and solutions

In reviewing the AI output, a LLM displayed satisfactory performance in retrieving and presenting top-level CDR concepts from reputable sources without confabulation or fabricated results. The outputs clearly summarised and quoted fundamental CDR concepts from existing open-access information provided by Bing Search. However, the Critical Agent-style prompting approach was required to elicit in-depth CDR insights and explanations beyond pulling quotes from sources and presenting basic top-level information. Information pertaining to specific CDR concepts (e.g., outlining specific privacy, fairness, and ethical concerns) could not be generated without employing the Critical Agent approach. This in turn indicates that a typical consumer with limited experience or knowledge of AI prompt engineering may not receive important information regarding actual and specific CDR risks and concerns that they may be exposed to from LLM usage. As such, this paper recognises that a minimum level of AI literacy is required among consumers to sufficiently prompt LLMs to present detailed information regarding the CDR risks and concerns they are exposed to. This need for AI literacy may create a knowledge and comprehension gap involving CDR risks and liabilities between AI literate and non-literate consumers. Service firms may be required to overcome this gap and avoid marginalising certain consumers by creating parameters for LLMs to provide detailed output covering CDR concerns and risks for basic one-shot prompts (e.g., "How is <Service firm> using my data?").

When prompted to provide specific recommendations for consumers to limit their exposure to CDR risks, the LLM output failed to provide any CDR-specific content. The output instead stated that the model did not possess the functional capability to identify and serve specific recommendations for consumers. Instead, generalist and top-level solutions were provided in the prompt (e.g., being mindful of sharing personal information, reading privacy policy statements, maintaining awareness of digital legislation and personal rights, etc.). The authors could not ascertain if this was an algorithmic and/or technical limitation, or the result of deliberate algorithmic guardrails to avoid assuming potential legal liabilities in providing actionable advice to consumers. In any respect, this limitation indicates that LLM-enabled service offerings may require improved algorithmic guardrails or safeguards that guide the LLM to provide pre-determined responses when prompted to provide CDR recommendations to its users. In doing this, the service firm may sufficiently outline the potential CDR risks that consumers face in using their LLM-enabled service offering and fulfil any duty of care

obligations, ensuring consumers receive adequate transparency from firms toward the CDR risks they are potentially exposed to by LLM usage (thereby mitigating potential fairness concerns).

4.2. Identification of original and novel CDR insights by LLMs

Existing cross-disciplinary research posits that LLMs such as GPT-4 are technologically incapable of generating new and novel research insights that provide sufficient conceptual development to be accepted by peer-reviewed journals (Dwivedi et al., 2023). The AI-prompted output obtained in this paper affirms that LLMs are functionally incapable of independently producing new and novel CDR insights at present time, at least not without very substantial editing and enhancement by human writers. However, the quality of the obtained top-level CDR insights produced by BingChat does affirm that LLMs can function sufficiently as academic writing tools and assist with specific tasks such as proof-reading, writing top-level summaries such as article abstracts, and retrieval of key sources (Golan et al., 2023). While LLMs could be utilised as a viable tool to assist academic writers for certain tasks, LLMs currently cannot operate as stand-alone academic writers due to the algorithmic limitations and dependence on existing data and textual associations to create output.

As identified within both outputs dedicated to generation of novel CDR insights, LLMs were functionally incapable of synthesising or identifying new types of CDR solutions or recommendations outside of those already known in service literature or practice:

I'm sorry, but as an AI language model, I don't have the ability to identify new solutions that service firms can employ to manage Corporate Digital Responsibility risks. My responses are based on information that is available online and in existing literature.

This result highlights the algorithmic limitations that prevent LLM's from producing new and novel insights as existing non-proprietary data or parameters are required for LLMs to generate output (Wu et al., 2022). Although LLMs may assist researchers in communicating new knowledge if the information is defined within an AI prompt, human operators with domain knowledge and expertise are still required to synthesise or recognise novel insights drawn from multiple sources of information. As Stadler and Reeves (2023) remarked in relation to this algorithmic limitation within consulting applications, "*Such tools are, therefore, no substitute for the cultivation of strategic minds*".

4.3. Discussion of collaborative prompt chain production method outcomes

The hybrid Chaining/Critical Agent approach to prompt generation was recognised to be a satisfactory method in prompting the LLM to provide top-level information within the conceptual context and academic writing style. Of the 50 total citations provided by the LLM across the 18 individual outputs (11 of which contained the seminal CDR article as outlined with an asterisk), only two sources were confabulated. One confabulated source referred to CDR as "Carbon Dioxide Removal" instead of Corporate Digital Responsibility, the other utilised Roger's Product Life Cycle model (Polli & Cook, 1969) instead of the CDR Data and Technology Lifecycle. No fabricated sources were identified in the final output, whereas an earlier draft of the prompt chain containing a reduced Critical Agent and Chaining focus had produced fabricated Wikipedia articles and other fake sources. The scaffolding approach had substantially reduced the observed level of confabulation and fabrication within the LLM output in comparison to initial prompt tests containing combined prompts.

However, the prompt construction approach taken in this paper still required further refinement and adaptation. For instance, it was recognised that the chaining method only functioned to a certain point. In the prompt pertaining to the CDR Data and Technology Lifecycle and privacy concerns, the LLM was unable to generate outputs containing ten or more concepts (CDR, the CDR Data and Technology Lifecycle, Adoption Stage, Operation Stage, Refinement Stage, Retirement State, Fairness, Ethics, Privacy). This issue occurred regardless of whether chained and scaffolded concepts were utilised or prompted in isolation with no prior

chained prompts. As such, this approach is potentially not adequate for analysing and summarising conceptual models or frameworks together.

Furthermore, the LLM would not follow word count specifications outlined in the prompt in some instances (e.g., *For your academic paper, please outline in 300 words how service firms can implement effective organisational solutions to manage Corporate Digital Responsibility trade-offs*). This was likely due to a lack of identified information or parameters pertaining to a particular prompt, although further refinement to the prompt construction process may provide a means to circumvent this issue.

It must also be noted that the Chain/Critical Agent prompt construction method is a viable approach for guiding LLMs in retrieval of top-level information involving academic and/or consulting models such as CDR, the CDR Data and Technology Life Cycle and the CDR Calculus. The Critical Agent aspect was recognised to be effective in establishing the correct context of the information and subject domain, alongside the required writing conventions and directing the LLM to prioritise usage of academic CDR sources. The authors encourage readers to trial the hybrid Chaining/Critical Agent approach in report writing and while providing educational instruction for AI usage, although this method cannot adequately produce academic-level or original insights that could be copied and submitted without further validation and substantiation.

4.4. Discussion of LLM output usage in peer-reviewed publications

The LLM output attained in this paper demonstrated that LLMs are technologically incapable of presenting output that is written to the standard required of manuscripts in peer-reviewed journals. LLM-enabled service offerings could be utilised for very specific applications during manuscript production (e.g., drafting abstracts, automatically retrieving key foundational sources for introduction and literature review sections, proof-reading entered text for spelling and grammatical errors). However, at present LLMs cannot match human intuition and judgement in producing original and novel insights from existing information. This is due to the recognised algorithmic dependence of LLMs to provide text based on predictive associations, coupled with a LLM's inability to create prompts containing new information attained from separate or previously unlinked concepts. Unless the retrieved data contains very specific attributes or tags, an LLM cannot produce new insights based on textual recognition alone.

Likewise, the AI interfaces of LLMs must be capable of attributing sources to specific insights within the output text. While this could be accomplished with existing information such as retrieved statistics, quotes and insights, the reliance on existing data and predictive associations within text may prevent LLM's from synthesising multiple attributed sources in text to form new and novel insights with these sources. Until a new class of algorithm emerges and is adopted by AI providers, LLM-based AI systems cannot synthesise multiple sources to create genuinely new insights within the service research context.

5. Conclusions

Our article is the first to explore the usage of AI-generated content in the CDR domain. As outlined in Table 2, the ability of LLM-based AI to produce information pertaining to CDR is heavily contingent on the level of AI literacy possessed by the consumer prompting the AI system. To circumvent this issue and ensure all consumers receive equal notice of the CDR risks and liabilities they face in using the system, dedicated parameters and guardrails must be implemented by service firms. Despite being autonomous service agents with the capability to independently source and provide information to consumers, the ability of LLM-enabled AI service systems to provide sufficient and accurate information is contingent on the inputs provided by human service actors.

Moreover, the findings affirm views advanced by leading authors within management academic community (Dwivedi et al. (2023) that LLM-based AI systems are unviable for producing new and novel insights at a standard required for academic research and passing peer-review processes. LLMs currently seem limited in how deeply

they analyse and synthesise content (especially in emergent and cross-disciplinary research such as CDR) to extrapolate theoretical understandings or synthesis of theories. Moreover, a new and improved class of AI algorithms will be required to overcome these current limitations and produce publishable academic content.

Table 2. Overview of key findings

Key finding	Implications
<p>RQ1: <i>Do LLM-enabled service offerings accurately convey information involving CDR concepts and concerns?</i></p> <p>Without existing guardrails and parameters incorporated within LLM systems, consumers require a minimum level of AI literacy to receive full notice of the CDR risks and liabilities they face.</p>	<p>Despite functioning as an autonomous service agent, LLMs cannot adequately inform all consumers of the CDR risks they may experience while using the system. To ensure all consumers can receive equal and fair warning of CDR risks and liabilities they are exposed to during usage of LLM-enabled service offerings, service providers must implement dedicated parameters in the LLM to provide consumers with sufficient information involving CDR risks and concerns.</p>
<p>RQ2: <i>Can service-focused LLMs identify novel methods for managing CDR trade-offs identified by the CDR calculus?</i></p> <p>RQ4: <i>Is an AI-prompt writing process a viable method of producing content for peer-reviewed publications in emergent service literature?</i></p> <p>LLM-based AI systems are incapable of identifying new and novel concepts within emergent domains and cannot produce sufficient contributions to service literature.</p>	<p>Due to the reliance of LLM-based service systems (and LLM-based AI at large) on drawing predictive textual associations from existing information, LLMs were found to be incapable at producing new and novel conceptual insights in emergent literature domain of CDR. This finding affirms perceptions held among journal authors in the business research domain toward the technical limitations of LLMs in producing sufficiently publishable material for journal manuscripts (Dwivedi et al., 2023).</p> <p>As these limitations are based on the underlying predictive algorithms used by LLM systems, these limitations are fundamental in nature and cannot be resolved by infinitely expanding the amount of training data and computing power given to the LLM.</p> <p>For certain tasks such as structural drafting, finding key sources, summarising top-level information, writing abstracts, and providing proof-reading services, LLMs are viable as academic writing tools.</p>
<p>RQ3: <i>Using the emergent domain of CDR in service as a basis, can LLMs be directed to produce content that advances the scope of academic knowledge?</i></p> <p>Demonstrated effectiveness of hybrid prompting approach. Human operators maintain a critical role in the functionality and operation of LLM-based AI systems in enacting AI quality control procedures, monitoring for potential CDR issues such as biases, and ensuring correct interpretation of AI input and output.</p>	<p>The hybrid chaining and critical agent AI prompting approach found to be effective in setting information context and task parameters, alongside reducing instances of fabricated sources provided in the AI output and confabulated insights involving irrelevant sources of information.</p> <p>Using a team of human specialists to create a prompt chain demonstrated preliminary effectiveness in identifying different issues within prompt chains based on emergent concepts and domains of information.</p> <p>A team of domain experts is required to ascertain instances of fabricated and/or confabulated findings in the data, due to the algorithmic and predictive limitations of LLM systems.</p>

Furthermore, the hybrid chaining and critical agent approach to AI prompt production displayed preliminary success in reducing output errors and improving the applicability of AI output within specific knowledge domains and contexts. Table 1 contains an overview of this hybrid AI prompt generation process, with written examples. Further refinements to this AI prompt production process should aim to take advantage of new and emergent functionalities afforded by LLM-based AI systems (e.g., sentiment tracking and interpretation, cross-platform integration, non-text-based input systems, etc.). The authors encourage readers to experiment with this AI prompt production approach and incorporate these techniques into their own AI-focused workflows.

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