Empowering co-creation of services with artificial intelligence: an empirical analysis to examine adoption intention

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Abstract
Purpose – Co-creation of services (CCOS) is a collaborative strategy that emphasises customer involvement and their expertise to increase the value of the service experience. In the service ecosystem, artificial intelligence (AI) plays a key role in value co-creation. Therefore, this study is undertaken to empirically uncover how AI can empower CCOS.

Design/methodology/approach – The source data were collected from 305 service provider respondents and quantitative methodology was applied for data analysis.

Findings – New service development augmented with AI provides tangible value to service providers while also providing intangible value to supportive customers. With AI, service providers adapt to new innovations and enrich additional information, which eventually outperforms human-created services.

Research limitations/implications – AI adoption for CCOS empowerment in service businesses brings "service-market fit", which represents the significant benefits wherein customers contribute to creativity, intuition, and contextual awareness of services, and AI contributes to large-scale service-related analysis by handling volumes of data, service personalisation, and more time to focus on challenging problems of the market.

Originality/value – This study presents theoretical concepts on AI-empowered CCOS, AI technological innovativeness, customer participation in human-AI interaction, AI-powered customer expertise, and perceived benefits in CCOS, and subsequently discusses the CCOS empowerment framework. Then, it proposes a novel conceptual model based on the theoretical concepts and empirically measures and validates the intention to adopt AI for CCOS empowerment. Overall, the study contributes to novel insight on empowering service co-creation with AI.

Keywords  Artificial intelligence, Co-creation of services, Human-AI interaction, Adoption intention, Service provider, AI-powered customer expertise

Paper type  Research paper

1. Introduction
In a highly competitive environment, businesses need to be aware of their customers’ needs, and therefore, conscious efforts must be made to attract and retain such customers (Belhadi et al., 2023). For this purpose, co-creation activities (i.e., co-creation of services) can be used to facilitate interaction between businesses and customers (Wei et al., 2019). Co-creation of services (CCOS) is defined as the value of a service that is created collaboratively by pulling
together customers and service organisations (Grönroos, 2012). CCOS is important since interactions between customers and businesses are what cause individuals to have personal reactions (Sarmento et al., 2024; Moliner-Tena et al., 2023). In addition to customers, CCOS can be done with other stakeholders, including employees, suppliers, competitors, and prospective buyers, by using a platform that allows stakeholders to exchange ideas, and be informed about any co-creation activities like designing and executing a process, and learning from it.

In continuation, such stakeholders’ involvement can pose challenges for CCOS, such as increasing complexity and uncertainty, compromising quality and consistency, and creating conflict and tension. Therefore, a technology-driven approach can act as a driver for CCOS empowerment and provide results that could not otherwise have been obtained without its adoption. Moreover, the implementation of information technology (IT) fosters service co-creation (Knani et al., 2022), and artificial intelligence (AI) as IT cannot be an exception. AI is described as IT that gathers, processes, and provides useable information (Paschen et al., 2020), which has been hailed as a boon to both customers and businesses (Grewal et al., 2021). The primary force behind the adoption of AI is value co-creation (Xu et al., 2023; Thaichon et al., 2020). Therefore, the above discussion justifies the need for an empirical analysis of the adoption intention of AI for empowering CCOS.

CCOS has been highlighted in the literature, i.e. unconscious procedural elements are present during the co-creation of the customer journey (for which the physical and cognitive abilities of the customer are required), which affects how the consumer perceives the quality of the service (Moliner-Tena et al., 2023). In the CCOS process, value is solely determined by the customer, and co-creation itself is fundamentally an “interactional creation” through which value is collaboratively expanded (Lee et al., 2023). Customers’ experiences could be significantly impacted if CCOS does not live up to their expectations (Bai et al., 2023a). Customer satisfaction and CCOS are closely related (Bai et al., 2023b).

Given the aforementioned arguments, the literature gaps are as follows: (1) there is a lack of literature in CCOS that has discussed an AI-enabled CCOS empowerment framework; (2) discussed theoretical concepts of customer participation in human-AI interaction, AI-powered customer expertise, and perceived benefits in CCOS empowerment context; (3) empirically assessed the lack of knowledge on correlation of AI technological innovativeness, customer participation in human-AI interaction, and AI-powered customer expertise with CCOS empowerment, CCOS empowerment and perceived benefits, perceived benefits and the adoption intention of AI, and the moderator role of willingness to co-create between customer participation in human-AI interaction and CCOS empowerment. Therefore, this study strongly argues that the above research gaps are important and, subsequently, call for an empirical investigation owing to the need for future research, and research problematisation on CCOS.

Moreover, the literature has highlighted the need for future research on CCOS, i.e., to capture co-creation from various perspectives, further research is needed that takes into account other actors (other than collaborators, owners, and moderators) in the service ecosystem (Bidar et al., 2021). Future research is required to examine the CCOS from the perspective of perceived benefits (Khan and Krishnan, 2021). Concerning research problematisation, the CCOS, where customers like to interact with the business, has not received enough attention (Cheung and To, 2021). In addition, this study argues that without AI, CCOS empowerment with an infusion of technology would not be possible. The lack of AI infusion into services can have negative effects that not all customers are willing to accept. Therefore, the convincing motivation for this study is justified by the literature gaps, the need for future research, the need for AI infusion, and the problematisation of research.

The scope of this study is to determine why the service provider intends to adopt AI in CCOS empowerment with active customer participation and their expertise for a variety of
benefits. Therefore, answers to the following research questions (RQs) are looked at to close the literature gaps:

**RQ1.** How do the drivers, including AI technological innovativeness, customer participation in human-AI interaction, and AI-powered customer expertise, influence CCOS empowerment?

**RQ2.** How does AI-enabled CCOS empowerment influence perceived benefits?

**RQ3.** How does perceived benefit influence AI adoption intention?

The novelties of the study are to: provide theoretical concepts on CCOS empowerment, AI technological innovativeness, customer participation in human-AI interaction, and AI-powered customer expertise; propose a novel conceptual model; and empirically measure and validate the proposed correlation in reference to literature gaps.

After the Introduction, the remaining sections are structured as follows: The theoretical background is discussed in Section 2. The hypotheses are developed in Section 3, followed by research methodology in Section 4. This follows the results in Section 5 and the discussion in Section 6. Lastly, Section 7 concludes the study.

### 2. Theoretical background

This study provides a novel perspective on empowering the CCOS with AI that necessitates the need for a theoretical foundation. Therefore, it discusses theoretical concepts including CCOS empowerment, AI technological innovativeness, customer participation in human-AI interaction, AI-powered customer expertise, and perceived benefits. Subsequently, it proposes an AI-enabled CCOS empowerment framework and a unique conceptual model. Owing to “service-market fit”, this study strongly argues for the correlation among the theoretical concepts. The “service-market fit” expresses the indisputable market demand for the services a business provides, as evidenced by customers buying, using, and recommending it to their friends. An empowered CCOS can help marketers better understand their customers, differentiate their services from competitors, reduce costs and risks, and foster long-lasting partnerships with customers, which can result in “service-market fit”. Individuals that enjoy taking chances and attempting novel approaches to problem-solving are usually encouraged to be the first to own or create a new technology-based service for a market (Thakur et al., 2016), and hence AI technological innovativeness can result in “service-market fit”.

In continuation, for the customers, an empowered CCOS can improve their satisfaction, engagement, empowerment, and trust in the service for a given market, and hence customer participation in human-AI interaction can result in “service-market fit”. There have been recurring investigations into how customer expertise affects service quality, which in turn affects their satisfaction, loyalty, and trust towards the service (Zhang et al., 2019), and hence AI-powered customer expertise can result in “service-market fit”. The perceived benefits of AI empowered CCOS can be to: unlock new perspectives wherein a customer can provide a new viewpoint to a problem or issue that has been raised; offer open participation and collaboration; enhance the generation of ideas and opportunities; enhance teamwork and community; enhance service transparency, trust, and authenticity; and produce shared value. Hence, perceived benefits can result in “service-market fit”. In addition, the AI-enabled CCOS empowerment framework discusses how empowered CCOS, AI technological innovativeness, customer participation in human-AI interaction, and AI-powered customer expertise can be blended to produce benefits that can enable service businesses to adopt AI. The conceptual model represents the theoretical concepts in the form of constructs for empirical validation.
2.1 Co-creation of services empowerment
Service co-creation entails the involvement and participation of at least one customer and one service provider, which can result in both positive and negative outcomes via resource integration (Oertzen et al., 2018). In brief, it is a development approach where customers are actively involved, use their expertise in AI, and take part in the design, development, and alteration of new or existing offerings in the service. The co-creation of services has become a routine phenomenon in the marketplace (Wei et al., 2019). Hence, service co-creation empowerment involves helping service firms and their customers make decisions that benefit both. Therefore, this study highlights numerous stages in CCOS empowerment, such as (Oertzen et al., 2018) co-ideation, co-valuation, co-design, co-test, and co-launch, that servitisation businesses can use. The stages can help a service provider consistently deliver the services, resulting in the desired experience and outcome for customers.

In co-ideation, a service provider can build an idea with the customers rather than seek out customers for the idea. This stage assures that the service provider is actually filling a market demand, rather than merely relying on the presumptions and prejudices of the team. In co-valuation, the service provider may decide to continue working with the same customers from the first stage to figure things out or may invite other customers to the valuation to seek answers on which service concepts would be most influential, feasible, or difficult for rivals to copy. In co-design, it is vital to avoid wasting time and resources on a service’s full development before it has received any input from the market. Therefore, the service provider must focus on the most crucial features during this stage to build, test, and iterate progressively. In co-test, the service provider must allow the customers to test the service and its features after their creation and receive their unfiltered feedback. The service provider must be careful to decide which specific features make feedback collection necessary and how to collect such feedback. In co-launch, the service provider must create a reliable network in the desired industry that includes not just customers and end users but also key influencers who can help the market’s tech-savvy, forward-thinking early adopters spread the word and foster favourable word-of-mouth.

A service provider continuously looks in both directions, i.e., exploration to plan for the innovations that will shape the future for new possibilities and exploitation to enhance the existing services for old certainties. As a result, a service provider demonstrates organisational ambidexterity in service co-creation when it separates responsible stakeholders in improving existing services from those who innovate new services (Sok and O’Cass, 2015). Literature suggests that technologically advanced organisations’ primary competency is organisational ambidexterity (Abdullah et al., 2022). Moreover, organisational ambidexterity can enhance the ability to understand and adapt to changes under challenging circumstances (Stokes et al., 2019). For effective exploration, the service provider must encompass knowledge creation and analysis of future opportunities, and for effective exploitation, it must include strategies like choice, refinement, production, selection, execution efficiency, and implementation intentions in the services. Therefore, the above discussion resembles the notation of “service-market fit”.

2.2 AI technological innovativeness
Technological innovativeness is a personal trait that indicates an individual’s desire to experiment with new technology (Gunness et al., 2023; Hur et al., 2017). In essence, it is a domain-specific innovation and is significant because it precisely predicts creative consumer behaviour (Thakur et al., 2016). It ranges from common ideas to cutting-edge technologies that open up new technological domains and organisations’ abilities to develop technologically significant or important innovations (Scherer and Ross, 1990). It is especially important for service dynamism, and factors such as curiosity, creativity,
expertise, and enthusiasm of the individuals engaged, as well as other demographic and psychographic characteristics, all influence the propensity for technological innovativeness (Klein and Bhagat, 2016). Furthermore, it is also a significant concept that has attracted research attention (Ding and Ding, 2022) and influenced the growth of the business (Qian and Wang, 2020). Given the aforementioned arguments, this study defines AI technological innovativeness as the extent to which the service provider adopts, adapts, and uses AI technologies that are significant to the optimum level of new service design and development and the alteration of existing services.

Following the line of thought in Bawack et al. (2021), this study proposed four major competencies of AI technological innovativeness, including perceptual experience, understanding, action, and learning, for a positive effect in the service ecosystem. Perceptual experience indicates that AI could be used for distinguishing objects such as images and videos, listening by capturing sounds such as an individual’s words, and/or observing other changes around where it is found. A number of different technologies, such as speech and image recognition systems, sensor technologies, and biometrics, could be used to provide AI systems with these perception capabilities. Furthermore, service providers can rely on other specific fields of AI, such as natural language processing (NLP), knowledge representation, and computer vision, as well as digitisation and methodology know-how, to provide AI systems with the capability, which can then be supplemented by image and video processing and text analysis to improve it even further. To improve this capability, image processing, video processing, and text analysis techniques can also be used.

In continuation, understanding means the relationship between individuals, objects, places, and occurrences should be capable of being represented and understood (i.e., making sense of facts in the service context and taking into account the customers’ intents) by AI. The service providers can rely on a large volume of data and leverage machine learning (ML) algorithms to extract relationships among variables to understand context-aware relationships. The action characteristic indicates that AI must be capable of taking action by interacting with customers in a normal manner. Service providers ensure that AI systems work through cooperating user interfaces, including chatbots and virtual assistants in conversational and collaborative AI systems. The learning characteristics indicate that AI can be able to learn by developing, improving, and adapting its expertise. ML and deep learning (DL) are the foundations of modern AI learning capabilities, and service providers ensure that such capabilities are available. This study argues that AI competencies enable service co-creation by inferring from literature.

One of the most important characteristics of AI is its potential contribution to co-creation service processes (Leone et al., 2021). The service provider must focus on customer involvement, and with the introduction of AI, customers can enjoy the services, increase their engagement time, gain trust, and improve the brand value of the services. The building blocks for AI in customer involvement are data unification (i.e., to merge the data from diversified sources and get the best out of it) and real-time insight delivery (i.e., analysing the interests of the customers). The AI-related technologies that make customer involvement possible are NLP (through the analysis of the customer voice and then enabling bots to transfer the spoken words to another language) and computer vision (through services like face detection and auto-subtitle generators from the images and videos). AI-enabled frameworks consisting of DL with the use of multimedia inputs such as texts and images and layer-wise relevance propagation (LRP) promote customer engagement (Yang and Lin, 2022). Therefore, the above discussion resembles the notation of “service-market fit”.

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2.3 Customer participation in human-AI interaction in CCOS empowerment

Most businesses are eager to encourage customer participation, which is seen as a crucial tool for improving productivity (Nyadzayo et al., 2023; Vargo and Lusch, 2016) and bringing brands closer to customers (Fang et al., 2011). Customers participate in the CCOS and contribute to the delivery phase by exchanging knowledge, informing personal requirements, making recommendations, and participating in the decision-making process (Auh et al., 2019). There is also amplifying research on the drivers of customer participation and its effects (Sadighha et al., 2024; Nardi et al., 2020). However, it is under-researched, and further studies are needed to fill the gap in the literature (Yi et al., 2021), and in the context of CCOS empowerment, it is not an exception.

In continuation, the service ecosystem includes human participation with technology-infused experiences within institutional frameworks to enable the CCOS (Peters et al., 2016). This analogy can be well-suited to human-AI interaction in the CCOS (Jiang et al., 2022). The goal of human-AI interaction is to improve models by incorporating human feedback during model training (Calisto et al., 2022). Human-centric interaction has been emphasised in the literature for the need to adapt and integrate information systems (IS) with human behaviour (Jain et al., 2022). Customer participation increases purchase and revisit intentions when AI is present (Zhang et al., 2021). An example of human-AI interaction is AI-aided decision-making, where the idea of using AI to help decisions sounds not just appealing but also rational (Crompton, 2021). Therefore, this study argues that in CCOS empowerment, customer participation in human-AI interaction involves providing positive feedback and suggestions on the services, and the enablement of AI-powered services delivers personalised marketing, sales, and service. In doing so, the customers not only express concerns or gratitude for the services, but also offer suggestions for new features or even a new service. Therefore, the above discussion resembles the notation of “service-market fit”.

2.4 AI-powered customer expertise in CCOS empowerment

In technical or highly specialised services, such as banking (Hosseini et al., 2022; Eisingerich and Bell, 2008) and retailing (Joy et al., 2023; Jamal and Anastasiadou, 2009), customer expertise is stressed. Customer expertise has been explored with respect to perceived technical or functional service quality (Eisingerich and Bell, 2008), which influences trust (Eisingerich and Bell, 2008), loyalty (Jamal and Anastasiadou, 2009), and satisfaction (Jamal and Anastasiadou, 2009). Customer satisfaction is uncertain due to the intangibility and non-standardisation of service (Murray and Schlacter, 1990), which is exacerbated by the nature of customer expertise (Zhang et al., 2019). Technical service quality improves as a result of customer expertise, which has a greater impact on customer loyalty decisions (Bell and Eisingerich, 2007). However, the impact of AI-powered customer expertise in CCOS empowerment scenarios has received no attention.

The CCOS is conducted using technology with the goal of realising a value proposition (Hilton et al., 2012). Therefore, this study argues that one of the trends in customer expertise in CCOS empowerment is IT, and the intersection of customer expertise and AI (called “AI-powered customer expertise”) is indispensable. The CCOS empowers AI-powered customer expertise to make automated decisions based on data and information analysis, and further observations of trends affect marketing efforts in the design, development, and alteration of services. Since AI holds a vital role in helping service providers connect with customers, choosing the right platform to match customer expertise is a critical first step in launching an AI campaign for CCOS empowerment. The service provider can be careful to identify the loopholes the AI platform is attempting to address and choose solutions based on customer expertise. Therefore, the above discussion resembles the notation of “service-market fit”.

2.5 Perceived benefits in CCOS empowerment

Beliefs regarding the positive outcomes associated with behaviour in response to a real or perceived threat are known as “perceived benefits” (Ahn and Kwon, 2022; Chandon et al., 2000), and it refers to a person’s perception of the benefits that will emerge in satisfaction as a result of engaging in a specific action (Liu et al., 2013). Customers evaluate a service’s function or performance based on perceived benefits (Leclercq-Vandelannoitte, 2015), and service benefits are a key component in adoption behaviour (Chang et al., 2017). Prior research has demonstrated that perceived benefits have a favourable impact on a business’s adoption of technology (Beatty et al., 2001), and the perceived benefits of the technology determine its adoption (Tarek et al., 2017). Greater customer participation in value creation processes leads to the integration of their skills and knowledge, resulting in the development of new and crucial capacities (Prahalad and Ramaswamy, 2004) as well as competitive advantage sources (Zhang and Chen, 2008). In addition, customer engagement is positively impacted by service quality, which is one of the service’s primary benefits (Kim et al., 2023); customer satisfaction is significantly determined by how customers perceive the benefits (Uzir et al., 2021); and research has historically shown a strong correlation between perceived benefits in the form of consumer performance expectations and usage intentions (Hamzah et al., 2023).

Following the above line of thought, this study proposes the five dimensions of perceived benefits in relation to CCOS empowerment, i.e. personal benefits (Zhang et al., 2020), social benefits (Ahn and Kwon, 2022), hedonic benefits (Tseng et al., 2021), cognitive benefits (Wisker, 2020), and pragmatic benefits (Walker and Baker, 2000). The personal benefits refer to the benefits in terms of status and recognition that customers receive from CCOS empowerment. The social benefit refers to the benefits in terms of being open and available to others and indulging in social connection with other customers on the common ground of CCOS empowerment. The hedonic benefits refer to the benefits in terms of experiencing pleasurable experiences from CCOS empowerment. The cognitive benefits refer to the benefits in terms of new service-based knowledge or AI skills gained from CCOS empowerment. The pragmatic benefits refer to the benefits in terms of better meeting personal needs through CCOS empowerment. Therefore, the above discussion resembles the notation of “service-market fit”.

2.6 CCOS empowerment framework

Based on the discussion on CCOS empowerment, AI technological innovativeness, customer participation in human-AI interaction, AI-powered customer expertise, and perceived benefits, this study proposed an AI-enabled CCOS empowerment framework (see Figure 1). The service industry is changing, and every day it becomes more vital to get customers to take active roles in their CCOS (Yen, 2023). Therefore, the AI-enabled CCOS empowerment framework is a critical component to help service organisations make informed decisions about the future of their businesses. The empowerment framework depicts the blending of customer resource, AI-based technology platform, and organisational ambidexterity covering exploration and exploitation to achieve customer benefits for a market, which resembles the notation of “service-market fit”. In addition, the framework is grounded on the bright side of AI over the dark side to achieve the desired benefits. The bright side of AI resembles the novel ideas and honourable intentions that lead to desired outcomes, which in turn help in the constructive evolution of humanity. The dark sides of AI are associated with challenges and risks. The challenges include privacy issues, data security, and ethical dilemmas. The risks include customer readiness for AI, human-AI interaction, and its adoption. However, the dark side of AI is out of the scope of this study.
2.7 Proposed conceptual model

In the literature, conceptual models based on CCOS have been proposed. The service co-creation on social media model (SCCoSM) by Namisango et al. (2021) describes the types, dimensions, and service co-creation metrics made possible by social media use in the non-profit sector. It has not considered the perceived benefits construct and thus lacks the ability to identify the consequences of professional services. The CCOS integrated framework (CCOSIF) by Oertzen et al. (2018) explores the factors that influence users’ behaviour during the CCOS as well as the factors that influence their involvement in such efforts. It has not considered the AI technological innovativeness construct and is thus unable to address the technological infusion of service. The nexus of co-creation model on social media (NoCCMoSM) by Jalonen et al. (2021) examines the potential of social media for fostering CCOS in the public sector. It has not considered the AI-powered customer expertise and AI technological innovativeness constructs, and thus lacks the justification to justify the validity of AI analysis and the generalisation of the findings.

In a similar vein, Bidar et al. (2021) develop a co-creation process from a network perspective theoretical model (CCPiNPTM) that depicts environmental cues and value judgements that influence online network service co-creation behaviour. It has not considered customer participation in human-AI interaction, AI-powered customer expertise, willingness to co-create, and has not discussed investigating the impacts of customer churn or negative word of mouth in future research. However, technology acceptance models, including the Technology Acceptance Model (TAM) (Davis, 1989), the Technology Acceptance Model 2 (TAM2) (Venkatesh and Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), the Technology Acceptance Model 3 (TAM3) (Venkatesh and Bala, 2008), the Diffusion of Innovation Theory (DIT) (Rogers et al., 2014), the Theory of Reasoned Action (TRA) (Fishbein, 1979), the Social Cognitive Theory (SCT) (Bandura, 1986), and the Information Systems Success Model (ISSM) (DeLone and McLean, 1992) were not developed exclusively for CCOS and hence were not considered. To summarise, Table 1 capture the underpinning models and their main drawbacks.

To sum up, the existing model has not discussed perceived benefits through the lens of CCOS dimensions or AI adoption intention, and therefore, this study strongly advocates for consideration of a unique conceptual model. The constructs (except AI technological innovativeness, customer participation in human-AI interaction, and AI-powered customer expertise) defined in Table 2 are discussed in silos, and establishing a structural relationship will add new knowledge to the field of service information systems and service management.
and can provide a range of findings with theoretical and managerial implications. This study introduces new constructs: AI technological innovativeness, customer participation in human-AI interaction, AI-powered customer expertise, CCOS empowerment, adapted willingness to co-create, perceived benefits, and adoption intention from existing literature. Each construct’s operational definition is listed in Table 2.

The rationale behind the consideration of constructs is discussed. The impact of technological innovativeness on behavioural intention is significant (Zwain, 2019), and the study argues that AI technological innovativeness will positively influence CCOS empowerment. Actively soliciting and encouraging customer participation in human-AI interaction has a number of benefits for businesses (Merlo et al., 2014). AI-powered customer expertise is a deciding factor in how service expectations are set and service delivery evaluations are made (Garry, 2008). Because of customers’ increased interest and the growing number of service organisations enabling customers to participate in the service innovation process, CCOS has gained a lot of attention in service innovation research (Sarmah et al., 2017). Perceived benefits increase the likelihood of an intention to use a service

<table>
<thead>
<tr>
<th>Conceptual model</th>
<th>Drawbacks</th>
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<tbody>
<tr>
<td>SCCoSM (Namisango et al., 2021)</td>
<td>It does not take into account the perceived benefits construct. Therefore, it lacks theoretical attention to better customer experience and streamlining processes in CCOS empowerment</td>
</tr>
<tr>
<td>CCOSIF (Oertzen et al., 2018)</td>
<td>It does not take into account the AI technological innovativeness construct. Therefore, it lacks theoretical attention to maintain flexibility and adaptability to changes in the market to obtain a competitive edge in CCOS empowerment</td>
</tr>
<tr>
<td>NoCCMoSM (Jalonen et al., 2021)</td>
<td>It does not take into account the AI-powered customer expertise and AI technological innovativeness constructs. Therefore, it lacks theoretical attention to increase customer touchpoints efficiency in CCOS empowerment</td>
</tr>
<tr>
<td>CCPfNPTM (Bidar et al., 2021)</td>
<td>It does not take into account customer participation in human-AI interaction, AI-powered customer expertise, and willingness to co-create constructs. Therefore, it lacks theoretical attention to cultivate meaningful and constructive interactions that advance knowledge and collaboration between customers and AI systems in CCOS empowerment</td>
</tr>
<tr>
<td>TAM (Davis, 1989), TAM2 (Venkatesh and Davis, 2000), UTAUT (Venkatesh et al., 2003), TAM3 (Venkatesh and Bala, 2008), DIT (Rogers et al., 2014), TRA (Fishbein, 1979), SCT (Bandura, 1986), ISSM (DeLone and McLean, 1992)</td>
<td>It does not take into account the CCOS. Therefore, it lacks theoretical attention to gain value on better products based on customer desires, new and unexpected ideas, the removal of barriers, differentiating offerings from competitors, enhancing customer satisfaction, involvement, empowerment, and trust in the brand, and the generation of positive word-of-mouth, referrals, and recommendations in CCOS empowerment. In addition, such models do not take AI into account. AI can deeply understand the interaction between service providers and customers to identify where and how CCOS can occur and can warn against superficial approaches that might render CCOS a concept without substance</td>
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Source(s): Authors’ own creation
The intention to adopt modern technologies determines the effectiveness and efficiency of technology-enhanced learning (Tarhini et al., 2014). Regardless of the service type, willingness to co-create is a strong predictor of intended co-creation behaviours (Neghina et al., 2017).

The discussions centred on the lack of appropriate constructs in the existing models, gaps in research owing to the non-availability of fitting constructs, and the benefits of establishing a structural relationship amongst such constructs, all of which justified the novelty of the conceptual model. Consequently, Figure 2 depicts the conceptual model based on the constructs defined in Table 1 and highlights hypotheses.

In the model, hypotheses H1 to H5 reflect the direct effect, whereas H6 represents the moderating effect. Firmographics, including firm size and firm age, are included in the

Table 2. Construct’s operational definition

<table>
<thead>
<tr>
<th>Construct</th>
<th>Operational definition</th>
<th>Reference</th>
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<tbody>
<tr>
<td>AI technological innovativeness (AITI)</td>
<td>The extent to which a customer is motivated to use AI-based services for value co-creation in service</td>
<td>Bruner and Kumar (2007)</td>
</tr>
<tr>
<td>Customer participation in human-AI interaction (CP)</td>
<td>Customers’ active participation in service encounters and interactions with AI that has an impact on the specificity, production, delivery, and consequences of the service provided</td>
<td>Wattanakamolchum (2008)</td>
</tr>
<tr>
<td>AI-powered customer expertise (CE)</td>
<td>Customers’ expertise in using AI to successfully perform service-related tasks and their understanding of various service categories attributes</td>
<td>Jamal and Anastasiadou (2009)</td>
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<tr>
<td>Co-creation of services empowerment (CCOS)</td>
<td>Collaborative empowered activities, which require customer and service provider involvement, engagement, and participation, which can result in favourable and/or detrimental consequences as a result of resource integration</td>
<td>Oertzen et al. (2018)</td>
</tr>
<tr>
<td>Perceived benefits (PB)</td>
<td>Beliefs about the positive outcomes associated with a behaviour of value co-creation in response to AI-based services</td>
<td>Chandon et al. (2000)</td>
</tr>
<tr>
<td>Adoption intention (ADI)</td>
<td>Extent to which the customers intend to adopt AI-based services in collaborative service design, development, and enhancement processes</td>
<td>Song et al. (2022)</td>
</tr>
<tr>
<td>Willingness to co-create (WTCC)</td>
<td>The extent to which customers are willing to integrate their own resources with service providers</td>
<td>O’Hern and Rindfleisch (2017), Arnould et al. (2014)</td>
</tr>
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Source(s): Authors’ own creation

Figure 2. Proposed conceptual model

Source(s): Authors own creation
conceptual model as covariates. The rationales behind consideration of such covariates are as follows: The firm size conveys to the customer that it can be trusted by taking into account both its overall size and market share position (Yu and Tung, 2014). Various business performance indexes are impacted by firm age (Lin et al., 2021).

3. Hypotheses development

In this study, the outcomes of the hypotheses are used to validate the RQs. Therefore, RQ1 is validated by H1 to H3, RQ2 by H4, and RQ3 by H5. Each hypothesis is developed below.

3.1 **AI technological innovativeness and CCOS empowerment**

CCOS empowerment can be a top priority for any service business. Keeping existing customers satisfied pays off significantly more for service businesses than constantly looking for new ones. AI is increasingly assisting businesses in improving service, customer loyalty, and brand reputation, as well as allowing staff to focus on higher-value jobs with higher returns. Research suggests the upshot of CCOS is value realisation, which can be acknowledged directly or implicitly (Vargo and Lusch, 2016), and the primary impetus for AI adoption intention is the realisation of economic value (Ashok et al., 2022). AI's ability to facilitate online conversation through chatbots to advance digital services such as personalised investment advice and fraud detection is becoming more widely recognised (Holmstrom, 2021). This study advocates that as AI becomes more widely utilised, the potential consequences for CCOS empowerment become more apparent in unexpectedly useful ways for the markets. The above discussion resembles the notation of “service-market fit” between AI technological innovativeness and CCOS empowerment. As a result, the following hypothesis is proposed:

\[ H1. \text{ AI technological innovativeness positively influences CCOS empowerment.} \]

3.2 **Customer participation in human-AI interaction and CCOS empowerment**

Customer participation in CCOS empowerment uses the consumer base’s opinions and ideas to generate new and inventive ideas for a service provider. Customers’ active participation in human-AI interaction during CCOS empowerment has an impact on the specificity, production, delivery, and outcomes of the service provided. Research suggests that customers will value their encounters with a service provider if they believe the service is relevant, meaningful, important, and valuable to them (Cheung and To, 2021). As a result of positive experiences in human-AI interaction, customers are dedicated to continuing to work with the service provider, such as by exchanging information with service people, making additional suggestions for service enhancement, and participating more actively in the CCOS (Behnam et al., 2021). This study advocates that customer participation in human-AI interaction is critical for guaranteeing quality, promoting best practices, and keeping services focused on how to best support excellent outcomes. To ensure that services meet human rights and the right to safety, customer participation in human-AI interaction must be established in accordance with market standards. The above discussion resembles the notation of “service-market fit” between customer participation in human-AI interaction and CCOS empowerment. As a result, the following hypothesis is proposed:

\[ H2. \text{ Customer participation in human-AI interaction positively influences CCOS empowerment.} \]

3.3 **AI-powered customer expertise and CCOS empowerment**

AI-powered customer expertise in CCOS empowerment can lead to great innovations, i.e., new service ideas, solutions to service delivery chain challenges, and even technological solutions
to complex questions. However, the expertise of the customers in the CCOS empowerment must be targeted and specific to the service provider, require trust and transparency, and may require motivation from the service provider. Research has examined how AI-powered customer expertise leads to a higher level of ability to contribute to service production (Auh et al., 2007). When a customer is reliant on a service provider, satisfaction with the customer’s expertise, the service provider’s expertise, communication, and interpersonal relationships may be a driving force for co-creation (Wang et al., 2015). This study advocates that AI-powered customer expertise touches on many dimensions of CCOS empowerment and impacts income growth. A customer expertise for a specific market strategy lays out the specific plans needed to provide a positive, valuable, and distinct service experience. The above discussion resembles the notation of “service-market fit” between AI-powered customer expertise and CCOS empowerment. As a result, the following hypothesis is proposed:

**H3.** AI-powered customer expertise positively influences CCOS empowerment.

### 3.4 Empowered co-creation of services and perceived benefits

To maximise the competitive advantage that an empowered CCOS offers to the service provider, it is important to quantify the perceived benefits. In doing so, the customers would have a greater appreciation for the service offering when the perceived benefits were identified and presented. Research suggests that participating in CCOS activities can be motivated by perceived benefits (Roberts et al., 2014). CCOS improves service quality and customer satisfaction while saving business costs (Gallan et al., 2013). These benefits explain why businesses are increasingly encouraging customers to participate in the CCOS (Mende et al., 2017). This study advocates that an empowered CCOS improves profitability, owns the customer interface, and reinvents the service offering. The service provider of a specific market must understand the shifting needs of customers in order to reap these benefits, and they must grow new services beyond their core offering. The above discussion resembles the notation of “service-market fit” between AI-enabled empowered CCOS and perceived benefits. As a result, the following hypothesis is proposed:

**H4.** The greater the level of AI-enabled empowered CCOS, the greater the perceived benefits.

### 3.5 Perceived benefits and adoption intention

The adoption of AI is rapidly taking hold across service providers to solve business problems. The advancement of a service provider’s digitalisation journey is a major facilitator of AI, and the businesses that have advanced the furthest in digitising fundamental business operations are also at the forefront of AI adoption. Research suggests an individual’s adoption and non-adoption intentions are influenced by perceived benefits (Chen et al., 2020). Perceived benefits influence adoption intention (Zulu et al., 2022). It has been observed that perceived benefits enhance the likelihood of an intention to use a service (Wang and Farquhar, 2018). This study advocates that AI developments in service providers present time-saving benefits by increasing productivity and improving efficiency in executing specific tasks related to service design, development, and remodelling for a specific market. The above discussion resembles the notation of “service-market fit” between AI-enabled perceived benefits and AI adoption intention. As a result, the following hypothesis is proposed:

**H5.** The greater the perceived benefits of AI-enabled empowered CCOS, the greater the adoption intention of AI.
3.6 Moderating role of willingness to co-create

A service provider must provide customers with high-quality services that help them reach their goals. Customer integration is a component of customer relationship management that employs AI technology to enable customers to combine their own resources with those of service providers in order to co-create services and maintain direct connections with service providers. Research suggests the most crucial component in the CCOS is the customer’s willingness (Jain et al., 2021). By devoting valuable time and effort, a customer with a high level of involvement leverages his knowledge (e.g., human-AI interaction) and ideas to develop a new service concept (Fernandes and Remelhe, 2016). This study advocates that when service providers are practicing customer integration and are willing to integrate their own resources for CCOS empowerment, it communicates a customer-centric mindset. This customer-centric mindset can help the business establish and maintain a great reputation in the marketplace. As a result, the following hypothesis is proposed:

H6. The willingness to co-create moderates the relationship between customer participation in human-AI interaction and AI-enabled CCOS empowerment.

4. Methodology

To assure the validity, reliability, generalisability, and dominance of the empirical inquiries, quantitative analysis should be used (Aytaç, 2021). Therefore, this study adopts a quantitative research methodology. As per Hair et al. (2016), structural equation modelling (SEM) was used as the proposed conceptual model is grounded on multiple relationships among the outcomes. Therefore, this study employs covariance-based SEM (CB-SEM), an alternative to variance-based SEM (VB-SEM), because the goal is to test the hypothetical constructs rather than theory building (Hew et al., 2019).

4.1 Data source

The data source was service providers based in India in the categories of cloud service, network service, payment service, telecommunications service, online service, and Internet service. The distinguishing feature was a group of experts on technology and service design, development, and remodelling with the consultation of customers, which plays a central role from beginning to end. They also allow customers to submit their ideas and opinions to bring fresh and innovative service concepts to the business. The rationale behind considering India as the data source is as follows, i.e., India is an emerging economy (Behera et al., 2023) that has pioneered service innovations (Wirtz et al., 2022). Furthermore, the services industry not only accounts for the majority of India’s GDP, but it has also attracted significant foreign investment, contributed significantly to exports, and created a significant number of jobs.

In continuation, the benefits of conducting empirical studies in the emerging economy or markets are highlighted in the literature, i.e. as businesses in the emerging economy expand their operations and presence globally, they produce global data about their customers, which can present additional research and theory opportunities and additionally lead to global competition (Sheth, 2011). Growth in digital payment technologies is mostly driven by the emerging economy (Adhikary et al., 2021). More research in the emerging economy is required to enhance marketing as an academic discipline and preserve its managerial relevance (Burgess and Steenkamp, 2006). In contrast to mature markets, emerging markets are regional, fragmented, frequently small-scale, and dominated by family-owned enterprises wherein customer attitudes and perceptions are influenced by the environment and culture of the home country (Mainardes et al., 2020), which resembles the potential for high growth.
Since findings in mature markets may not be generalisable, specific research in emerging markets is necessary (Mainardes et al., 2017).

4.2 Data collection procedure
Quantitative data were gathered in two periods: Period 1 (December 2022–March 2023) and Period 2 (April 2023–June 2023) using an online survey. The consent form and participant information sheets were provided to the respondents who indicated their willingness to participate in this study. Five interviewers performed the survey via video call. The study recommends that five interviewers are sufficient, as each of them spends one to two hours with each participant. For both periods, the surveys were conducted via video calls (i.e., video surveys). In Period 1, around 20% of the data were collected to check the functioning of the research model, and the output of Period 1 was used to improve the effectiveness of measurement instruments for Period 2 i.e., to make the questionnaire easier for responders to understand and complete quickly, a few minor language composition improvements were made. In Period 2, the remaining 80% of the data were collected. The respondents who participated in Period 1 did not participate in Period 2, but their consents were taken into account due to the minor changes to measurement instruments.

4.3 Respondents’ profile
Table 3 lists the respondents as well as their firm (i.e., service provider) profiles. According to the table, 54% of the firms have less than ten years of existence, 35% employ between 250 and 499 employees, and 25% are network service providers. The table also shows that 65% of respondents collaborate with firms that are less than ten years old, and 28% of respondents collaborate with network service provider firms.

4.4 Sampling
The firms were identified using simple random sampling, which was followed by the use of snowball sampling for the collection of respondent responses. The population comprised

<table>
<thead>
<tr>
<th>Characteristics</th>
<th># of firms</th>
<th>Firm proportion</th>
<th># of respondent</th>
<th>Respondent proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Firm size</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1–49</td>
<td>15</td>
<td>29%</td>
<td>99</td>
<td>32%</td>
</tr>
<tr>
<td>50–249</td>
<td>20</td>
<td>39%</td>
<td>109</td>
<td>36%</td>
</tr>
<tr>
<td>More than 250</td>
<td>17</td>
<td>32%</td>
<td>97</td>
<td>32%</td>
</tr>
<tr>
<td><strong>Firm type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloud service provider</td>
<td>12</td>
<td>23%</td>
<td>75</td>
<td>24%</td>
</tr>
<tr>
<td>Network service provider</td>
<td>13</td>
<td>25%</td>
<td>85</td>
<td>28%</td>
</tr>
<tr>
<td>Payment service provider</td>
<td>5</td>
<td>10%</td>
<td>25</td>
<td>8%</td>
</tr>
<tr>
<td>Telecommunications service provider</td>
<td>7</td>
<td>13%</td>
<td>30</td>
<td>10%</td>
</tr>
<tr>
<td>Online service provider</td>
<td>6</td>
<td>11%</td>
<td>20</td>
<td>7%</td>
</tr>
<tr>
<td>Internet service provider</td>
<td>9</td>
<td>17%</td>
<td>70</td>
<td>23%</td>
</tr>
<tr>
<td><strong>Firm age</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Until 10 years</td>
<td>28</td>
<td>54%</td>
<td>149</td>
<td>49%</td>
</tr>
<tr>
<td>More than 10 years</td>
<td>24</td>
<td>46%</td>
<td>156</td>
<td>51%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>52</td>
<td>100%</td>
<td>305</td>
<td>100%</td>
</tr>
</tbody>
</table>

*Table 3. Firms and respondents profile*

*Source(s): Authors’ own creation*
service provider firms operating out of India and the customers of such firms. As recommended by Ochieng et al. (2024), targeted founders and senior-level managers of service provider firms were contacted via email, LinkedIn, and Facebook as they were thought to have the necessary strategic and operational knowledge on CCOS. Consequently, a total of 60 service providers and, 1285 people volunteered to take part in the survey. After removing duplicate, irrelevant, unwanted, missing, and structural error data, a total of 305 valid respondents and 52 firms’ responses were taken into consideration for analysis. As per Hair et al. (2006), the sample size should be in the range of 200–400 when SEM is used as a data analysis tool, and the sample size for this study was 305.

4.5 Measurement instruments
For service providers and their customers, a five-point Likert scale questionnaire was developed. Table A1 of Appendix captures the details of the questionnaire. As recommended by Chatterjee et al. (2022), the five-point Likert scale was chosen because it is simple to use, takes less time and effort to complete, and additionally, respondents have the option of selecting “neither disagree nor agree” to remain neutral on this scale. However, existing literature-based measures were used to develop the questionnaire, and a pre-test was done to reduce the phrasing and formats of the questions to make them easier to understand. The study used a qualitative approach to validate the pre-existing measurement items to operationalise the constructs in the context of AI-enabled CCOS empowerment in the service industry.

In continuation, the semi-structured questionnaire was created using a mix of deductive and inductive methods. The respondents were questioned on each construct (inductive) after taking into account the measurement items from the literature (deductive), and the findings were then collated. Each qualitative response was carefully examined, and the study discovered that it could be divided into three items. Consequently, the AITI items were adapted from (Bruner and Kumar, 2007), the CP items from (Groth, 2005), the CE items from (Bell and Eisingerich, 2007), the CCOS items from (Pappas et al., 2017), the PB items from (Cheng et al., 2021), the ADI items from (Song et al., 2022), and the WTCC items from (Etgar, 2008).

4.6 Common method bias (CMB)
Due to the sample respondents’ bias, this survey has CMB (Podsakoff et al., 2003). Prior to the data analysis (Malhotra et al., 2006), Harman’s single-factor test was used to evaluate CMB, which might affect the validity of the results. It states that the estimated cumulative variance value should be below 50%, and this study has produced 35.82%, which demonstrates the absence of CMB. Furthermore, the average inter-item correlation (r) was used to assess internal consistency and reliability. As per Piedmont (2014), “r” should be in the range of 0.20–0.40, and this study reports 0.307, which indicates homogeneous items. As recommended by Safeer et al. (2021), to evaluate the full collinearity of data, this study further uses the variance inflation factor (VIF), which directs the evaluation of lateral and vertical collinearity in tandem. No bias in the data is revealed by VIF values under 3 (Safeer et al., 2021). This study found VIF values of less than 3.0, which indicated no collinearity issues or CMB threat in the data.

5. Results
As per the suggestion by Anderson and Gerbing (1988), this study uses a measurement model and a structural model.
5.1 Measurement model
According to Hair et al. (2006), convergent reliability considered in the measurement model is Achieved when factor loading (FL), average variance extracted value (AVE) values are greater than 0.50. As per Fornell and Larcker (1981), internal reliability considered in the measurement model is achieved when Cronbach’s alpha (CA), and composite reliability (CR) values are greater than 0.70. For CB-SEM to be effective, the data must be ideally or nearly normally distributed, and to determine it, skewness and kurtosis are evaluated, with ideal values falling between $-2$ and $+2$ (Dash and Paul, 2021). Table 4 shows the constructs’ FL, AVE values are greater than 0.50, and their CA, CR values are greater than 0.70. The table also shows that skewness and kurtosis values are within the threshold range. Therefore, this result justifies its validity.

To validate the discriminant validity, the Fornell-Larcker and Heterotrait-Monotrait (HTMT) criteria are used. As per Fornell and Larcker (1981), the Fornell-Larcker criterion is satisfied when the square root of AVE for each construct must be greater than its highest correlation with the other constructs. As shown in Table 5, all the diagonal elements were

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
<th>FL</th>
<th>CA</th>
<th>CR</th>
<th>AVE</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>AITI</td>
<td>AITI1</td>
<td>0.835</td>
<td>0.795</td>
<td>0.794</td>
<td>0.750</td>
<td>0.386</td>
<td>-0.918</td>
</tr>
<tr>
<td></td>
<td>AITI2</td>
<td>0.802</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AITI3</td>
<td>0.767</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CP</td>
<td>CP1</td>
<td>0.763</td>
<td>0.708</td>
<td>0.734</td>
<td>0.508</td>
<td>0.111</td>
<td>-0.611</td>
</tr>
<tr>
<td></td>
<td>CP2</td>
<td>0.766</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CP3</td>
<td>0.725</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CE</td>
<td>CE1</td>
<td>0.803</td>
<td>0.808</td>
<td>0.810</td>
<td>0.588</td>
<td>-0.224</td>
<td>-0.307</td>
</tr>
<tr>
<td></td>
<td>CE2</td>
<td>0.831</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CE3</td>
<td>0.749</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCOS</td>
<td>CCOS1</td>
<td>0.657</td>
<td>0.871</td>
<td>0.872</td>
<td>0.695</td>
<td>-0.071</td>
<td>-0.667</td>
</tr>
<tr>
<td></td>
<td>CCOS2</td>
<td>0.687</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CCOS3</td>
<td>0.678</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>PB1</td>
<td>0.790</td>
<td>0.871</td>
<td>0.879</td>
<td>0.710</td>
<td>0.112</td>
<td>-0.737</td>
</tr>
<tr>
<td></td>
<td>PB2</td>
<td>0.747</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PB3</td>
<td>0.818</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADI</td>
<td>ADI1</td>
<td>0.757</td>
<td>0.842</td>
<td>0.841</td>
<td>0.640</td>
<td>0.507</td>
<td>-0.771</td>
</tr>
<tr>
<td></td>
<td>ADI2</td>
<td>0.699</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ADI3</td>
<td>0.763</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTCC</td>
<td>WTCC1</td>
<td>0.817</td>
<td>0.813</td>
<td>0.817</td>
<td>0.599</td>
<td>-1.101</td>
<td>0.911</td>
</tr>
<tr>
<td></td>
<td>WTCC2</td>
<td>0.790</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WTCC3</td>
<td>0.820</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Convergent validity Source(s): Authors’ own creation

<table>
<thead>
<tr>
<th>Constructs</th>
<th>ADI</th>
<th>PB</th>
<th>CCOS</th>
<th>AITI</th>
<th>CP</th>
<th>CE</th>
<th>WTCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADI</td>
<td>0.800</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>0.792</td>
<td>0.842</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCOS</td>
<td>0.738</td>
<td>0.965</td>
<td>0.833</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AITI</td>
<td>0.452</td>
<td>0.390</td>
<td>0.382</td>
<td>0.750</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CP</td>
<td>0.534</td>
<td>0.409</td>
<td>0.310</td>
<td>0.206</td>
<td>0.713</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CE</td>
<td>0.532</td>
<td>0.471</td>
<td>0.567</td>
<td>0.279</td>
<td>0.470</td>
<td>0.767</td>
<td></td>
</tr>
<tr>
<td>WTCC</td>
<td>0.304</td>
<td>0.308</td>
<td>0.407</td>
<td>0.401</td>
<td>0.346</td>
<td>0.345</td>
<td>0.774</td>
</tr>
</tbody>
</table>

Table 5. Discriminant validity Source(s): Authors’ own creation
greater than the off-diagonal elements in the respective rows and columns, and all estimations of inter-correlation were lower than 0.792. According to Henseler et al. (2015), the HTMT criterion is satisfied when the square root of AVE for each construct is less than 0.90. As shown in Table 5, all the diagonal elements were less than 0.900. Therefore, such a result justifies discriminant validity.

There are two statistical tests that can be used to assess data factorability: the Bartlett’s test of sphericity (Bartlett, 1954) and the Kaiser-Meyer-Olkin (KMO) (Kaiser, 1970) measure of sample adequacy (Madanchian et al., 2018). According to the factor analysis evaluation criteria, the KMO index should be between 0 and 1, with 0.6 considered the minimal value of factor analysis, and at a $p$-value of less than 0.05, Bartlett’s test should be relevant (Taherdoost, 2016). Bartlett’s test of sphericity, which suggests statistical significance, supports the factorability of the correlation matrix (Madanchian et al., 2018). The sample was adequate for factor analysis because the statistical value of the KMO measure of sampling adequacy was 0.880, which was higher than the minimum value of 0.6. The value of the Chi-square of Bartlett’s test is 3345.489, the value of DF is 210, the value of Chi-square/DF is 15.930, and the significance value is 0.000 (i.e., the $p$-value of less than 0.001).

5.2 Structural model
A statistically significant $p$-value of less than 0.05 indicates that the hypothesis is supported (Grabowski, 2016). The direct effect is summarised in Table 6, which justifies the support for hypotheses H1 to H5. The relationship between the explanatory and response variables that have been hypothesised is represented by the path coefficient ($\beta$).

The model fit indices are shown in Table 7 and are considered to be excellent fits.

The effect of the moderator (i.e., WTCC) is summarised in Table 8, which justifies the support for H6. Following Marsh et al. (2004) recommended matched-pairs approach, the moderating hypothesis was investigated. The matched pairs are used to create product indicators for the terms of interaction between an independent and moderator variable in order to estimate the latent interaction (i.e., CP x WTCC → CCOS) (Leo et al., 2022). The structural equation model then included the interaction term.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Relation</th>
<th>Std. Error</th>
<th>t-value</th>
<th>$\beta$</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>AITI → CCOS</td>
<td>0.058</td>
<td>3.609</td>
<td>0.25</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>H2</td>
<td>CP → CCOS</td>
<td>0.067</td>
<td>4.879</td>
<td>0.32</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>H3</td>
<td>CE → CCOS</td>
<td>0.084</td>
<td>6.332</td>
<td>0.42</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>H4</td>
<td>CCOS → PB</td>
<td>0.076</td>
<td>10.957</td>
<td>0.69</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>H5</td>
<td>PB → ADI</td>
<td>0.060</td>
<td>11.179</td>
<td>0.81</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Source(s): Authors’ own creation

<table>
<thead>
<tr>
<th>Test</th>
<th>Value</th>
<th>Ref value</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMIN/DF</td>
<td>2.623</td>
<td>1–3</td>
<td>Hooper et al. (2008)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.073</td>
<td>&lt;0.08</td>
<td>Kline (2015)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.908</td>
<td>&gt;0.90</td>
<td>Hair et al. (1998)</td>
</tr>
<tr>
<td>TLI</td>
<td>0.894</td>
<td>&gt;0.90</td>
<td></td>
</tr>
<tr>
<td>IFI</td>
<td>0.909</td>
<td>&gt;0.90</td>
<td></td>
</tr>
<tr>
<td>NFI</td>
<td>0.861</td>
<td>&gt;0.90</td>
<td></td>
</tr>
</tbody>
</table>

Note(s): Ref value depicts reference value
Source(s): Authors’ own creation

Table 6. Hypotheses testing results of direct effect

Table 7. Model fit indices
Tables 9 and 10 represent the covariate effects of firm size and firm age on the relationship between perceived benefits and adoption intention. The multi-group evaluation criteria were used for the analysis of the covariate effect and capture the standard error, \( t \)-value, \( p \)-value, and \( R^2 \) of adoption intention. As per the suggestion by Anning-Dorson (2017) and Wang et al. (2020), the firm size was determined by the total number of full-time employees, and the firm age was determined by the number of years the firm had been operating. Consequently, the firm size was grouped into 1–49 (i.e., small), 50–249 (i.e., medium-sized), and more than 250 (large) as per the recommendation by Bordonaba-Juste et al. (2012). Following the suggestion by Wang et al. (2021), the participants holding senior management positions were recommended for the firm’s classification as until 10 years old (startup) and more than 10 years old (old).

From Table 9, it can be concluded that adoption intention does not differ among the firm size groups of small, medium, and large, i.e. firm size does not play a significant role in determining the adoption intention of AI in CCOS empowerment. This is primarily due to their openness to AI and data-driven decision-making. Such firms strongly believe that AI helps them grow business revenue, boost service efficiency, and improve the customer experience. However, from the \( R^2 \) value, it can be concluded that large firms have a better intention to adopt AI, followed by medium and small firms. Large firms consider AI to be poised to unleash the next wave of digital distribution. From Table 10, it can be concluded that adoption intention does not differ among the firm age groups of startup, and old, i.e. firm age does not play a significant role in determining the adoption intention of AI in CCOS empowerment. This is primarily due to their belief that AI can deliver real value to their business. However, from the \( R^2 \) value, it can be concluded that old firms have a better intention to adopt AI than startup. The old firms have better awareness of AI technologies or applications in their business operations. In addition, they provide knowledge on AI’s current and future organisational impact and barriers to deployment.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Relation</th>
<th>Std. Error</th>
<th>( t )-value</th>
<th>( p )-value</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>H6</td>
<td>CP ( \times ) WTCC ( \rightarrow ) CCOS</td>
<td>0.012</td>
<td>-5.193</td>
<td>&lt;0.001</td>
<td>0.596</td>
</tr>
<tr>
<td></td>
<td>WTCC ( \rightarrow ) CCOS</td>
<td>0.078</td>
<td>3.686</td>
<td>&lt;0.001</td>
<td>0.697</td>
</tr>
</tbody>
</table>

Source(s): Authors’ own creation

<table>
<thead>
<tr>
<th>Firm size</th>
<th>Std. Error</th>
<th>( t )-value</th>
<th>( p )-value</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>0.097</td>
<td>6.915</td>
<td>&lt;0.001</td>
<td>0.541</td>
</tr>
<tr>
<td>Medium</td>
<td>0.088</td>
<td>9.855</td>
<td>&lt;0.001</td>
<td>0.677</td>
</tr>
<tr>
<td>Large</td>
<td>0.127</td>
<td>7.235</td>
<td>&lt;0.001</td>
<td>0.701</td>
</tr>
</tbody>
</table>

Source(s): Authors’ own creation

<table>
<thead>
<tr>
<th>Firm age</th>
<th>Std. Error</th>
<th>( t )-value</th>
<th>( p )-value</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Startup</td>
<td>0.095</td>
<td>8.828</td>
<td>&lt;0.001</td>
<td>0.596</td>
</tr>
<tr>
<td>Old</td>
<td>0.079</td>
<td>10.262</td>
<td>&lt;0.001</td>
<td>0.697</td>
</tr>
</tbody>
</table>

Source(s): Authors’ own creation
6. Discussion
The primary goal of this study is to measure the adoption of AI in CCOS empowerment and witness the benefits. This study reported an $R^2$ value of 0.393 for CCOS empowerment, 0.482 for perceived benefits, and 0.656 for adoption intention. RQ1’s validity was confirmed with the support of H1 to H3, RQ2 with the support of H4, and RQ3 with the support of H5. The RQ1 validity addresses a research gap, i.e., empirical measurement of the structural relationship between AI technological innovativeness, customer participation in human-AI interaction, and AI-powered customer expertise with CCOS empowerment. The validity of RQ2 addresses a research gap, i.e., an empirical measurement of the structural relationship between AI-enabled CCOS and perceived benefits. The validity of RQ3 addresses a research gap, i.e., an empirical measurement of the structural relationship between perceived benefits and adoption intention of AI. The literature gap on customer participation in human-AI interaction, AI-powered customer expertise, and perceived benefits in the CCOS empowerment context is addressed with the comprehensive discussion in the theoretical foundation. The comprehensive discussion in the theoretical background fills the literature gap on the stages of service co-creation. As a result, service practitioners are advised to adopt AI for service co-creation empowerment.

The validity of the conceptual model has research implications. The AI adoption of CCOS empowerment in service firms brings “service-market fit” and its benefits can have a significant positive impact on service businesses and customers as a whole, i.e. customers offer creativity, intuition, and contextual awareness of services and with the adoption of AI by businesses, it contributes to large-scale service-related analysis by handling large volumes of data, service personalisation, and more time to focus on challenging problems of the market. The goal of the “service-market fit” is to align the service offerings of the businesses with the demands of the market, and this synergy gives the businesses the best chance of success while also offering customers real value. The demand for a better service is boosted by “service-market fit” (Kaufmann and Eroglu, 1999). An essential component of successful technology start-ups is the desired service in technology-based or digital entrepreneurship (Ajah et al., 2022). Value creation in the service ecosystem depends on giving attention to and involving customers (Sharma, 2021). Hence, AI adoption for CCOS empowerment can be of paramount important.

The study also validates the perceptions regarding the importance of technological innovativeness in CCOS from previous studies, and the finding is consistent with it, i.e. the dynamic contribution of the network environment on the Internet, co-creation settings, and customer interactions contribute to the co-creation of services (Bidar et al., 2021). Social media enables the dimension of co-creation of services (Namisango et al., 2021). CCOS is feasible with technology-enabled services and can occur within and between service systems (Windasari et al., 2021). Digital technologies have the ability to contribute to the co-creation of services (Jalonen et al., 2021). Similarly, other studies focused on customer participation, and the findings are in line with those, i.e. customer, technology, and organisational interaction are the driving forces for service co-creation (Akaka and Vargo, 2015). The majority of CCOS initiatives are dyadic, focused on interactions between frontline personnel and customers or the impact of the service context on experience formation (Jaakkola et al., 2015). So, AI and its related technology can be adopted and implemented by the service provider with the active participation of customers and their expertise to respond to modern-day service-related challenges.

6.1 Empirical findings
This study produces two key findings in the context of emerging markets. First, new service development augmented with AI offers tangible value (i.e., growth and profitability) to
service businesses and concurrently offers intangible value to supportive customers, corroborating H1, H2, H3, and H4. AI-driven COOS empowerment helps the service provider in three areas, i.e. market, prospects, and competitors. While targeting the market, the customer comes up with a luminous idea that allows the service provider to stay ahead of the competition and get more customers. While targeting prospects, the service provider makes a profile of clusters that are likely to use the service, and due to such clusters, they like the service and keep coming through word-of-mouth. Prospects are expected to be time-pressed and technologically savvy. While targeting competitors, the service provider figures out who they are, what they are doing well, and most importantly, what they are doing wrong. The best way to overtake the competitor is to provide high-quality service with the involvement of customers and their expertise. The finding confirms (Knani et al., 2022; Bendi et al., 2020) i.e., the CCOS supports strategic decision-making by evaluating the pros and cons of a specific situation based on customer participation and their expertise. This finding may differ from the developed markets wherein AI-driven COOS empowerment helps the service provider make the market, prospects, and competitors safer by fully meeting their standards. The practical relevance of strategic decision-making offers marketers a way to ensure a sustainable competitive advantage.

Second, a service provider’s business is dynamic, wherein the service offered to customers has to be revised based on their increasing wants and needs, corroborating H5. In such events, the business should spot the gaps from the market’s perspective and adapt its services. The process is seen as a less risky business option than launching a brand-new service. With NLP, ML, and DL, AI can dramatically improve service innovation management by potentially replacing human invention. The active participation of the customers and their expertise led to the adaptation of services with little support from service providers and technology evangelists due to technological innovativeness factors including: (1) AI generates innovativeness; (2) AI automates information processing and removes human dependency; (3) AI is a decision-making technology with the potential to automate a wide range of problem-solving tasks; and (4) DL is the next generation of AI that allows the machine to learn itself. The finding confirms (Malodia et al., 2023) i.e., AI generates new ideas that are innovative, fast, inexpensive, and AI-created services can outperform human-created services. This finding may differ from those in the developed markets, i.e., when the AI adoption digital divide broke out, developed market service firms could perform better than those in emerging markets. The practical relevance of AI-created services offers marketers the ability to ensure the execution of complex tasks without significant cost outlays, and facilitates decision-making by making the process faster and smarter.

6.2 Theoretical contributions
The study empowers CCOS with AI by examining adoption intention and proposing a CCOS empowerment framework and unique conceptual model. Based on the results of the study, it produces three interesting theoretical contributions to the field of IT, and service theory. According to MacLean and Titah (2023), a key and frequently used strategy for managing an organisation’s function and achieving both operational and strategic benefits is the use of IT in service management, and AI cannot be an exception. In fact, AI is being used extensively in the development and delivery of services with the goal of increasing overall performance by reducing costs and increasing efficiency (Huang and Gursoy, 2024). Therefore, each of the contributions bridges the gaps in literature by offering a more holistic perspective on adoption intention.

First, the study support Hypotheses H1, H4, and H5. Since, CCOS has evolved into a strategic option for businesses of all sizes and locations (Cheung and To, 2016), and hence this study coded AI-empowered CCOS into five stages, i.e. co-ideation, co-valuation, co-design, co-
test, and co-launch to ensure increased business benefits. A firm’s overall performance is improved by AI capabilities by digitally altering their processes (Mikalef et al., 2023), and hence this study coded four key capabilities of AI, i.e. perception, comprehension, action, and learning. To encourage positive attitudes and behavioural intents, it is essential to understand perceived benefits (Ahn and Kwon, 2022), and hence this study coded five dimensions of perceived benefits, i.e. personal benefits, social benefits, hedonic benefits, cognitive benefits, and pragmatic benefits. The aggregation of the dimensions and the key capabilities characterise the adoption intention of AI for CCOS empowerment due to its perceived benefits (see Figure 3). It can be concluded that the adoption of AI in CCOS empowerment generates value, and the value can come in the form of revenue generation and cost reduction at the functional level (e.g., service operation optimisation, predictive service and intervention, and new AI-based enhancements of services and customer service analytics) of the service provider. Therefore, this argument adds a new metaphor to service theory.

Second, the study supports Hypothesis H2. Hence, service feedback is crucial in shaping and improving it and can be sought at various touchpoints to better understand what is on a customer’s mind at any given time, which can provide insight into pain points and areas for improvement. To discover needs, promote co-creation, realise value for specific customers, and create experiences, customer participation is essential (Bharti et al., 2014). Moreover, the participation of customers in CCOS empowerment is becoming increasingly valuable, notably in the AI age. AI is the foundation for new capabilities, and firms must be able to properly implement and adopt it if they are to completely profit from its potential advantages (Haefner et al., 2023). Therefore, as a result of AI amplification, customers participate directly in defining, influencing, establishing, and co-creating platforms, initiatives, movements, and the branding of the services. However, it can be difficult for the service provider to find out how and where to incorporate customer participation in the service life cycle, and there is no right answer; the answer should be tailored to the business’s strategy and objectives. By integrating customer participation in human-AI interaction into the proposed conceptual model, this study suggests that customer participation in terms of effort, time, and other resources contributes to the service provider’s productive service capacity. This argument exemplifies sociological imagination in service theory.

Third, the study supports Hypothesis H6 and willingness to co-create (WTCC) moderate between AI technological innovativeness and CCOS empowerment. Literature has revealed that WTCC is an important component of co-creation (Vermehren et al., 2023). Moreover, empowerment increases WTCC (Wang et al., 2023). Therefore, WTCC represents the technological behavioural intention of the customer to empower CCOS. Essentially, customers must invest technological effort in the form of time, understanding and implementing AI-based solutions, and information sharing with businesses to empower CCOS. In return, they have the advantage of being able to design or customise the services to

![Figure 3. Key capabilities for AI adoption for co-creation of services empowerment](image-url)
suit their requirements and preferences. Customers’ readiness to participate in CCOS empowerment on an individual level is extremely desirable, since it could help identify and characterise those customers who are likely to exhibit high levels of WTCC. As a result, WTCC is based on the perceived benefits the customers believe they could receive. This argument adds an interesting speculative part to service theory.

6.3 Managerial implications
Based on the results, this study has two substantial practical implications for service managers in emerging markets. First, the outcome of the Hypothesis H1 suggests that the primary goal of designing and executing CCOS empowerment practices using the AI model is to achieve sustainable improvements. Utilising IT capabilities that are challenging for competitors to understand is necessary to achieve a lasting increase in competitive positioning (Doherty and Terry, 2009). Therefore, AI-enabled CCOS empowerment can ensure high-quality solutions that are delivered to customers in a consistent and sustained manner. Hence, a thoroughly planned sustainability strategy is essential to long-term success in the current business environment, where organisations are beginning to recognise the critical needs of customers by striking the ideal balance between financial, social, and environmental concerns. So, to provide a personalised service, service providers must offer solutions to their customer’s most complex problems, and these solutions must range from identifying risks to developing a strategy, from socio-economic impact assessment to responsible finance. Users can be empowered to make smarter decisions by receiving personalised services that cater to their demands (Mou et al., 2023). However, in developed markets, personalised service can happen at scale, and in emerging markets, it happens depending on the needs or wants of the customers.

Second, the outcome of the Hypothesis H3 suggests that AI-powered customer expertise lays out the actionable plans needed to provide constructive, priceless, and differentiated CCOS empowerment. For marketers and policymakers, customer expertise is the key (Zhang and Guo, 2021). Therefore, with AI-powered customer expertise, its lifecycle can be segmented into three groups, i.e. beginner, intermediate, and expert. The segmentation can be done with consideration of features including technical expertise in AI; and customer demographics, psychographics, behavioural patterns, and geographic. The beginners are the customers who have started using the services. The intermediates are the customers who have learned the service but have not mastered it yet. The experts are the customers, who know the service inside and outside. Customers begin as beginners and progress to experts through active participation, growing interest, and increased use of the service. So, it is crucial to know how many customers are at each level when designing a service. If the majority are experts, the service provider may be expected to add more advanced features to the service. If the number of intermediates grows rapidly, some advanced features may become too difficult to learn, and the service provider would need to make services easier to use. So, it is critical for the service provider to recognise the number of customers at each stage of the lifecycle.

6.4 Limitations and future research directions
This study has limitations and directions for future research. First, the proposed key capabilities of AI are grounded in technological trends. Since customer participation in human-AI interaction plays a driving role in CCOS empowerment, the capabilities of AI can be further classified based on Maslow’s hierarchy of needs. Needs are considered to be the foundation of motivation, and according to Maslow’s needs hierarchy theory, all human needs are classified into a five-part hierarchy, i.e., physiological, safety, social, esteem, and self-actualisation requirements (Chen et al., 2021). So, the study lacks discussion on the classification of AI based on customer needs and customer motivation.
Second, individual users are known to have varying degrees of willingness to adopt new technology (Nov and Ye, 2008), and several studies confirmed the importance of personal innovativeness in how early adopters can facilitate the adoption of new technology (Khazaei and Tareq, 2021). The study could not establish the moderator role of personal innovativeness between perceived benefits and adoption intention because we could not operationalise it in the context of CCOS empowerment.

Third, with the advancement of new technologies, it is important to investigate customers’ abilities to use these new technologies, and the concept of technology anxiety has been developed to understand the use of technology to accomplish goals (Meuter et al., 2003). Since AI is a self-service technology, the study could not explore its role due to a lack of understanding by the customers in the context of CCOS and a lack of data. Fourth, the study was conducted in the context of emerging markets, and its findings may not reflect the perspective of developed markets.

For future research, the study first proposes to theoretically investigate Maslow’s hierarchy of needs in the context of the CCOS and information systems to define the categorisation of AI. Subsequently, an empirical study can be performed to measure the adoption intention for such categories of AI. Second, a qualitative research and scale development approach can be conducted to operationalise personal innovativeness, and an empirical study can be performed to measure adoption intention. Third, we propose a better sample data selection in which customers have a good understanding of technology anxiety in the context of CCOS empowerment and then conduct an empirical study to measure adoption intention. Fourth, the study used the “bright side of AI”, and future research can explore the “dark side (i.e., disruptive, confusing, offensive, and unpredictable behaviours) of AI”, which can violate traditional human-computer interaction to investigate the impact of co-creation in the light of the co-creation of services. Fifth, future research can be conducted using the (Merkx and Nawijn, 2021) inductive approach by reviewing the digital contents in reviews and blogs on developed markets to extend the findings.

7. Conclusions
This study proposed a novel conceptual model with AI technological innovativeness, customer participation in human-AI interaction, and AI-powered customer expertise as independent variables, adoption intention as the dependent variable, and willingness to co-create as the moderator variable to measure the AI adoption intention for CCOS empowerment. A quantitative approach was used for the empirical analysis, and this study produced two findings. First, adding AI to new service development provides service organisations with actual benefits while also providing supportive customers with intangible value. Second, AI enables service providers to adapt to new developments and augment existing knowledge, ultimately outperforming services developed by humans. The co-creation of service empowerment is a fun version of jury duty in that everybody has the opportunity to share ideas, build AI-rendered models, examine prototypes, and offer constructive criticism during the group’s deliberations. Without AI, the empowerment of service co-creation cannot consider human-like functions like assisting customers in decision-making, reliability, precision, and personalisation in the service. This study, in particular, contributes to service marketing for the possible adoption of AI in CCOS empowerment.

References


(The Appendix follows overleaf)
Appendix

Table A1 contains five-point Likert scale questions, and the customers of Indian service providers were asked to respond to such questions.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Scale items</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>To adopt AI-based services in service design and development process and co-creation of services empowerment</strong></td>
<td>AITI1</td>
<td>I use AI-based services before most other people know it exists</td>
<td>Bruner and Kumar (2007)</td>
</tr>
<tr>
<td>AI Technological Innovativeness (AITI)</td>
<td>AITI2</td>
<td>It is cool to be the first to own AI-based services</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AITI3</td>
<td>Being the first to use AI-based services is very important to me</td>
<td></td>
</tr>
<tr>
<td><strong>To adopt AI-based services in service design and development process and co-creation of services empowerment</strong></td>
<td>CP1</td>
<td>I am willing to perform all the required tasks</td>
<td>Groth (2005)</td>
</tr>
<tr>
<td>Customer Participation in human-AI interaction (CP)</td>
<td>CP2</td>
<td>I am willing to fulfil responsibilities to the service organisation</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CP3</td>
<td>I am willing to adequately complete all expected behaviour</td>
<td></td>
</tr>
<tr>
<td><strong>To adopt AI-based services in service design and development process and co-creation of services empowerment</strong></td>
<td>CE1</td>
<td>Almost all the aspects of the services I receive from my provider are clear to me</td>
<td>Bell and Eisingerich (2007)</td>
</tr>
<tr>
<td>AI-powered customer Expertise (CE)</td>
<td>CE2</td>
<td>I possess good knowledge of services</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CE3</td>
<td>I am well acquainted with my provider’s services approaches and techniques</td>
<td></td>
</tr>
<tr>
<td><strong>To adopt AI-based services in service design and development process and co-creation of services empowerment</strong></td>
<td>CCOS1</td>
<td>I believe I am able to communicate with services and provide input on my preferences</td>
<td>Pappas et al. (2017)</td>
</tr>
<tr>
<td>Co-creation of Services empowerment (CCOS)</td>
<td>CCOS2</td>
<td>I believe I am capable of interacting with services and propose new ideas</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CCOS3</td>
<td>I believe my suggestions are in line with what is to be developed/changed in services</td>
<td></td>
</tr>
<tr>
<td><strong>To adopt AI-based services in service design and development process and co-creation of services empowerment with the consideration of five dimensions of perceived benefits, i.e. personal benefits, social benefits, hedonic benefits, cognitive benefits and pragmatic benefits</strong></td>
<td>PB1</td>
<td>Co-creation of services provides me with personalised services tailored to my activity context</td>
<td>Cheng et al. (2021)</td>
</tr>
<tr>
<td>Perceived Benefits (PB)</td>
<td>PB2</td>
<td>Co-creation of services provides me with more relevant service information tailored to my personal preferences or interests</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PB3</td>
<td>Co-creation of services provides me with the type of service I like</td>
<td></td>
</tr>
<tr>
<td><strong>To adopt AI-based services in service design and development process and co-creation of services empowerment</strong></td>
<td>ADI1</td>
<td>I am willing to adopt AI when choosing co-creation of services in the near future</td>
<td>Song et al. (2022)</td>
</tr>
<tr>
<td>Adoption Intention (ADI)</td>
<td>ADI2</td>
<td>I plan to adopt AI when choosing co-creation of services in the near future</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ADI3</td>
<td>I intend to adopt AI when choosing co-creation of services in the near future</td>
<td></td>
</tr>
</tbody>
</table>

Table A1.
Measurement items (continued)
Constructs | Items | Scale items | Source
---|---|---|---
To adopt AI-based services in service design and development process and co-creation of services empowerment (WTCC) | WTCC1 | In the near future, I am willing to work on a co-creation of services initiative | Etgar (2008)
 | WTCC2 | I am willing to dedicate time to the co-creation of services initiative |  
 | WTCC3 | I am willing to put effort into co-creation of services initiatives |  

Source(s): Authors’ own creation

Table A1.