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Exploring Value Co-Destruction Process in Customer Interactions with AI-Powered Mobile Applications

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Abstract

Background: *Mobile applications have emerged as important touchpoints for addressing service requests and optimizing human resources. Within the service industry, the integration of artificial intelligence (AI) into these applications has enabled the inference of product demand, provision of personalized service offers, and enhancement of overall firm value. Customers now engage with these apps to stay informed, seek guidance, and make purchases. It is important to recognize that the interactive and human-like qualities of AI can either foster the co-creation of value with customers or potentially lead to the co-destruction of customer value. Although prior research has examined the process of value co-creation, the present study aims to investigate the underlying factors contributing to the value co-destruction process, specifically within AI-powered mobile applications.*

Method: *Our research employs topic modelling and content analysis to examine the value co-destruction process that occurs when customers engage with AI apps. We analyze 7,608 negative reviews obtained from eleven AI apps available on Google Play and App Store AI apps.*

Results: *Our findings reveal six distinct types of value - utilitarian, hedonic, symbolic, social, epistemic, and economic value - that can be co-destroyed during the process. System failure, self-threat and privacy violation are some contributing factors to this value co-destruction process. These values change over time and vary depending on the type of app.*

Conclusion: *Theoretically, our findings extend the concept of value co-destruction in the context of AI apps. We also offer practical recommendations for designing an AI app in a more service-friendly way.*

Keywords: AI Apps, Value Co-destruction.

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Introduction

Artificial intelligence (AI) has changed the service delivery practice in both positive and negative ways (Bock et al., 2020). Customers often evaluate service quality through customer-employee contact quality, advice credibility, empathy, and responsiveness (Bock et al., 2020). However, the integration of AI agents (i.e., service robots, chatbots or AI-powered mobile apps) disrupts and contributes to each level of service interaction by giving additional resources for the value-creation process (Riikkinen et al., 2018). AI-powered apps can provide users with recommendations and answer their problems immediately (Kaartemo & Helkkula, 2018). At the same time, AI agents may co-destroy customer value by violating their privacy, lowering their self-esteem, and exploiting customers' money (Shin et al., 2020). For instance, customers who are unaware that they are engaging with a bot may feel as though they are being deceived. Customers could be irritated if AI agents ask inquiries that do not flow logically from previous interactions (Čaić et al., 2018; Canhoto & Clear, 2020). From the brand's standpoint, the AI agent may also undermine brand value by generating a response inconsistent with the brand's identity (Canhoto & Clear, 2020). The "good side" of emerging AI technologies is well-known, but the customer-robot interaction is loaded with issues and concerns.

While recent research on AI and service investigates both the bright and dark sides of AI in service interaction (Čaić et al., 2018; Chi et al., 2020), these studies primarily focus on the value co-creation process, leaving some aspects unexplored. First, value is not only co-created but may also be co-destroyed by customers and firms during their interactions (Čaić et al., 2018; Castillo et al., 2021; Hsu et al., 2021; Plé & Chumpitaz Cáceres, 2010). Second, AI agents have been studied for their supporting role in the value-creation process of customers instead of being the main actor in the service delivery process (Bock et al., 2020; Čaić et al., 2018; Riikkinen et al., 2018). AI is becoming more intelligent; thus, it has the potential to become an actor in "value creation through resource integration and service-for-service exchange" (Bock et al., 2020; Kaartemo & Helkkula, 2018). The resource integration process is more complicated; thus, there is a need to investigate how resources may be disintegrated during the process (Bock et al., 2020; Kaartemo & Helkkula, 2018; Vo et al., 2022).

Customers interact with AI apps in two ways: as a brand's touchpoint (i.e., branded app) or as an independent service (i.e., revenue-generating business app) (Chi et al., 2020; Tang, 2019). For example, a shopping app such as IKEA acts as a virtual shopping assistant that could scan the room to recommend suitable furniture for the living experience. Independent services such as Wysa could serve as a virtual counsellor that provides personalized mental health advice. With AI technologies, these apps learn from customer needs and preferences and enable resource integration between service providers and customers (Kaartemo & Helkkula, 2018). The virtual assistance delivered through these apps goes beyond a mere tool and could be considered an actor and resource integrator. Different from other AI-powered technologies, such as self-service kiosks and humanoid robots, AI-powered mobile apps are more familiar to customers (Fang, 2019). Customers engage with these apps daily to form an actor-to-actor network that creates value for each other (Fang, 2019). As such, investigating the AI app allows the researcher to examine the human-AI interaction, which may lead to value co-destruction in the service context.

This research focuses on how AI-powered mobile applications (AI apps) co-destroy value when customers engage with these apps. It explores the value formation process and examines the contributing factors of value co-destruction in the mobile AI app context, responding to recent calls for exploring AI and value co-destruction (Canhoto & Clear, 2020; Kaartemo & Helkkula, 2018). The study draws on the concepts of value co-destruction and consumption value to highlight various types of value that are co-destroyed during individuals' consumption experiences, as well as the factors contributing to such value co-destruction.

RQ: How is value co-destroyed when customers interact with AI-powered mobile applications?

We looked at 7,608 negative reviews written in English and posted online via Google Play or the App Store. These reviews are from eleven different AI-powered mobile applications. The deductive methodology is employed for the analysis of the data. Topic modelling is employed to automatically extract themes from a corpus (Ding et al., 2020). The results provide both topic-related keywords and proportional distributions of different topics across each document. This method enhances the qualitative interpretability of textual data by revealing the relationships between words in a corpus and offering extra insight into the connections between distinct themes. Then, the researcher combines LDA topic modelling with content analysis to have a closer look at each topic and further explore the meaning of each one.

The result of topic modelling and content analysis shows that six different types of value (utilitarian, hedonic, symbolic, social, epistemic, and economic value) can be co-destroyed in the process. These values change over time and vary depending on the type of app. For apps that employ intuitive intelligence, symbolic value is the customers' top concern. For apps that treat customers as a companion, most of their concerns are related to the co-destruction of economic value.

This study aims to respond to two knowledge gaps that were identified in previous research. First, the current literature on AI in service delivery has focused on value co-creation rather than value co-destruction (Manser Payne et al., 2021; Paschen et al., 2021). Even though a few researchers have explored the dark side of chatbots (Castillo et al., 2021), their research emphasized the link between customer resource loss, attributions of resource loss, and customer coping strategies rather than disintegration. Second, although much of the earlier research has focused on self-service technologies, chatbots, or service robots (Čaić et al., 2018; Castillo et al., 2021; Hsu et al., 2021), fewer studies have investigated the value of AI apps in general. Mobile applications, which behave as digital assistants, are becoming an increasingly important component of our day-to-day life. Unlike chatbots or service robots that are experts in specific tasks, AI apps could be used for diverse business objectives with various integrated functionalities (Mondal & Chakrabarti, 2019).

The next chapter discusses how customers, AI apps, and service providers may all be considered actors in the network. The concept of value co-destruction is then used to establish the theoretical foundation for the research. Using topic modelling and content analysis, we find six themes illustrating how interaction behaviors result in the loss of value. Theoretical and practical implications for human-AI app interaction and value co-destruction study are presented in the end.

Literature Review

In this study, AI apps refer to mobile applications that incorporate AI technology, and the AI agent acts as the frontline service employee that directly communicates with the customers. Theoretical underpinnings of mobile app research include a technology adoption model, expectation confirmation theory (Fang, 2019), uses and gratification theory (Alnawas & Aburub, 2016) to identify antecedents of intention to use such as perceived usefulness, value for money, or app rating (Prakash & Das, 2020). These theories assume that customers' adoption intentions are based on the expected achievement (Fang, 2019), which is not enough to explain consumers' engagement with the technology (Shang & Chiu, 2022). More recent studies have examined localization, ubiquity, interactivity (Fang, 2017), argument quality, source credibility, and parasocial interaction (Lee, 2018) to explain how customers obtain information, communicate with the firm, and engage in activities while using these apps.

AI and service literature has identified four types of intelligence: mechanical, analytical, intuitive, and empathetic (Huang & Rust, 2018). While mechanical intelligence has minimal learning or adaptation, analytical and intuitive intelligence could also be called "thinking AI" due to its advancement in identifying meaningful patterns, processing information and maximizing decision-making accuracy (Huang & Rust, 2021). Health-monitoring applications or guestroom comfort control are considered intuitive and intelligent (Chi et al., 2020; Pathak et al., 2020). Empathetic intelligence (feeling AI) describes a machine that can feel or at least behave as though it has feeling; it has interpersonal, social, and people skills that help recognize and understand customers' emotions (i.e., Replika, Sophia) (Huang & Rust, 2021). This is the most advanced generation of AI, and current applications to service are still very few. These levels of intelligence may be both ordinal and parallel. These types of intelligence will be adopted in different service situations, depending on the nature of the service.

Various levels of AI could be combined in several ways to cater to the nature of the service offering in the utilitarian-hedonic continuum and the transactional-relational continuum (Huang & Rust, 2021). Utilitarian service may naturally be suited for thinking AI, while hedonic service is considered high-touch and can benefit from feeling AI (Batra & Ahtola, 1991; Huang & Rust, 2021). While transactional service has little to gain from a customer relationship and will benefit more from mechanical AI replacement (Huang & Rust, 2021), relational service can benefit from having a solid relationship with customers because a higher customer lifetime value can be expected; thus, service providers should strive to use feeling AI (Huang & Rust, 2021). AI technologies are part of service functions, which have distinct roles and capabilities in delivering different types of services. For this study, we follow the framework of Huang and Rust (2021) and Huang and Rust (2018) to explore the customers' value co-destruction experience of different AI-powered apps.

Service is not simply an exchange of products; value is what both firms and customers co-create during their interaction (Hsu et al., 2021). Interaction occurs throughout the service delivery process. For instance, Echeverri and Sklén (2011) discovered that customers and service providers experience bad experiences during five interactions: informing, welcoming, delivering, billing, and assisting. These interactions make customers understand the attitudes and opinions of the service provided, which thus affect their consumption decisions (Dolan et al., 2019). Through this interaction, the value could be co-created or co-destroyed.

Value co-creation and value co-destruction may happen together during interaction (Elo et al., 2022; Li & Tuunanen, 2022). As value co-creation and value co-destruction are dynamic and activity-centric processes rather than an actor-centric process, where different types of resources are used and combined (Hauke-Lopes et al., 2022). For example, in traditional business, the value formation process is triggered by both digital and non-digital resources and mitigated by mutual reliance. As these resources integrate successfully, value co-creation happens and improves processes and capabilities in terms of digital development and traditional production. However, if digital resources are introduced without changes in other digitalization-related processes, frictions are caused, leading to value co-destruction (Hauke-Lopes et al., 2022). In the B2B context, value co-creation happens when alliance partners share resources and support value propositions, while value co-destruction can also happen due to conflictual interactions between alliance actors (Pathak et al., 2020).

In the context of AI apps, value is co-created or co-destroyed due to the success or failure of resource integration (Tran et al., 2021). For instance, Lim et al. (2021) recommended that customers co-create value with the app if it allows them to communicate their needs and co-create solutions with the firm. Customization, experience, and relationship are strongly connected with value in use, facilitating value co-creation (Tran et al., 2021). While traditional mobile applications assist the company in co-creating value with consumers, AI could be viewed as a critical actor in the value co-creation process (Paschen et al., 2021). At the same time, viewing AI apps as the main actor in the value formation process is worth investigating how and why customer values are co-destroyed, especially from the customers' perspective.

Value Co-destruction

Value co-destruction refers to *"an interactional process between service systems that results in the decline in at least one of the service systems' well-being (which can be individual or organizational well-being)"* (Plé & Chumpitaz Cáceres, 2010, p.431). Value co-destruction is a failed interaction process with a negative outcome; it leads to a decline in well-being, which can take the form of frustration or lost resources for a service provider or customer (Sthapit & Björk, 2019). Value destruction is not the absence of value creation; it is the devaluation of individuals' consumption experiences that diminishes their perceived value (Zainuddin et al., 2017). This state occurs when a consumer's value judgments become negative, and the features of a good/service are denigrated (Zainuddin et al., 2017). In other words, the destruction of value results from a difference between the firm's value propositions and the customer's perceived value during the service process (Plé & Chumpitaz Cáceres, 2010).

The value co-destruction process is triggered by both customers and the service system (Plé & Chumpitaz Cáceres, 2010). For example, a customer who buys a car but does not maintain it subsequently destroys the value they receive from owning the car. Customers also destroy the firm's value if they spread negative word of mouth (Plé & Chumpitaz Cáceres, 2010). Customers could intentionally misuse resources (i.e., the firm's resources and/or their resources) to obtain more value for themselves while co-destroying the value of the firm. For example, customers may demand that employees spend extra time servicing them, leading to the misuse of the company's resources, i.e., the employees. Although the misuse may be unintentional, the company suffers from the diminished efficiency of its employees, resulting in value co-destruction for the company (Plé & Chumpitaz Cáceres, 2010). In self-service technologies, customer collaboration goes wrong due to failures in the co-creation process. Therefore, value co-destruction happens due to the 'inabilities in co-learning', 'poor co-operation', 'problems with connecting' and 'poor corrective actions' (Galdolage, 2021).

Scholars often focus on two main streams of research on value co-destruction. One focuses on identifying practical activities in the value formation process that may cause value co-destruction. For example, Dolan et al. (2019) found three online complaints with potential value co-destruction. By analyzing guest reviews and host responses, Camilleri and Neuhofer (2017) found six elements of value co-destruction practices, including welcoming, evaluating location and accommodations, expressing feelings, helping, interacting, recommending, and thanking. Another stream of research focuses on the contributing factors and consequences of value co-destruction. For example, Järvi et al. (2018) identified that value co-destruction emerges due to the absence of information, an insufficient level of trust, the inability to serve and the lack of clear expectations. Zhang et al. (2018) showed that co-destruction emerges from rude employee behaviors, confrontation with company representatives, technological failure, the lack of complaint outlets, and customers' desire for revenge. This study is aligned with and complementary to the latter research stream, which aims to explore the contributing factors to value co-destruction.

Regarding human-robot interaction, customers may face value co-destruction processes when the social robots lead to undesirable consequences such as a loss of privacy, the stigma of disability, and fear of dependence (Čaić et al., 2018). For example, while customers perceive the robot as an enabler who makes them feel at ease by presenting by their side, they also see the robot as a violation of privacy that tracks their every move (Čaić et al., 2018). In other words, the robot is perceived to have value co-destruction potential because it interferes with the customers' privacy. In this case, elderly people express unwillingness to cooperate with the robot, and they denote the technology's invasiveness primarily through continuous interaction (Čaić et al., 2018). Previous research has found five antecedents of failed interactions between customers and chatbots, including authenticity issues, cognition challenges, affective issues, functionality issues, and integration conflicts (Castillo et al., 2021).

Researchers have acknowledged that value could be co-destroyed during the interaction (Plé, 2017; Echeverri & Skålén, 2011). We posit that value co-destruction occurs when a consumption experience is denigrated by the elements within that experience, which act as a hindrance. When there is a service failure, some forms of consumption value (i.e., utilitarian, hedonic, social, emotional, epistemic, and conditional) can be co-destroyed (Smith & Colgate, 2007). However, little is known about the value being co-destroyed and the factors contributing to the co-destruction of these values in AI-powered apps. The studies by Skourtis (2016) and Smith and Colgate (2007) identified different forms of consumption value that could be formed, co-created, or co-destroyed during the interaction process. However, they investigate neither how this value was co-destroyed nor the contributing factors of value co-destruction in the context of mobile apps. Therefore, our study aims to identify values that are co-destroyed during individuals' consumption experiences, as well as the factors that cause such value co-destruction.

Consumption Value

During the interaction between consumers and service providers, several types of value are created, for which the customers assess to make their purchase decisions (Sheth et al., 1991; Skourtis et al., 2016). The value includes utilitarian, hedonic, social, economic epistemic, symbolic, and experiential value (Skourtis et al., 2016; Smith & Colgate, 2007) (Table 1).

Table 1 – Type of Consumption Value

Consumption value	Definition	In the context of technology
Utilitarian value	The product's capacity for physical performance (Sheth et al., 1991)	Perceived usefulness (Tran et al., 2021); system quality (Tang, 2019), and perceived benefits (Prakash & Das, 2020).
Hedonic value	The ability to arouse feelings (Sheth et al., 1991)	Create feelings for users (Tran et al., 2021).
Social value	The affiliation with one or more distinct social groups (Sheth et al., 1991).	An app allows consumers to engage with external networks, or it may promote a personal interaction between the app's persona and its users (Tran et al., 2021).
Economic value	When customers see their purchase is valued for money (Sheth et al., 1991).	Occur when there are sales offers or reduced prices (Tran et al., 2021).
Epistemic value	The potential to excite curiosity, give novelty, and fulfil a demand for knowledge (Sheth et al., 1991; Smith & Colgate, 2007).	The capacity of mobile apps to help users become more aware of goods, and stay current on subjects they care about (Alnawas & Aburub, 2016)
Symbolic value	Consumer's sense of self (Sheth et al., 1991).	The threats to status, image, and identity (Frank et al., 2021).
Experiential value	The enhancement of customer experience (Fang, 2017)	An AI agent can provide a one-of-a-kind experience to customers through humanized interactions and personalization (Lim et al., 2021)

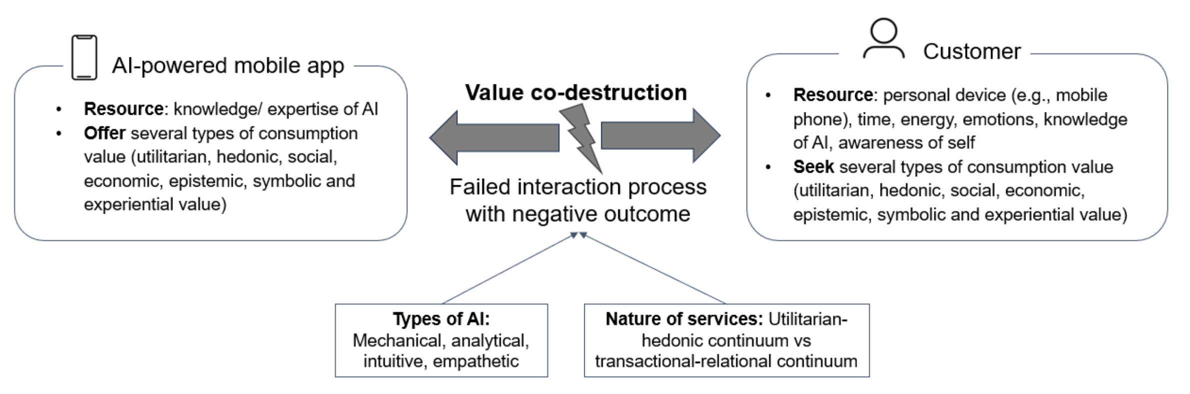
While utilitarian value is defined as the product's capacity for physical performance, hedonic value refers to the ability to arouse feelings (Sheth et al., 1991). The affiliation with one or more distinct social groupings is referred to as "social value." An app that provides social value may feature an online community that allows consumers to engage with external networks or promote a personal interaction between the app's persona and its users (Tran et al., 2021).

Economic value is created when customers see their purchase is valued for money, which could occur when there are sales offers or reduced prices (Sheth et al., 1991).

Recent studies have also explored epistemic, symbolic, and experiential value (Smith & Colgate, 2007). A product or service's epistemic value is determined by its potential to excite curiosity, give novelty, and fulfil a demand for knowledge (Sheth et al., 1991; Smith & Colgate, 2007). In the context of applications, epistemic value refers to the capacity of mobile apps to help users become more aware of goods, stay current on subjects they care about, and be stimulated to consider these topics in new ways (Alnawas & Aburub, 2016). In addition, symbolic value is also considered in the context of AI and marketing (Li et al., 2015). The usage of cutting-edge technology is associated with an innovative self-image and social image (Frank et al., 2021), which may increase the symbolic value of AI products. Nonetheless, delegating tasks to AI products may result in a loss of task-related control (André et al., 2017); or AI could threaten status, image, and identity, decreasing the consumer's sense of self (Frank et al., 2021). Experiential value refers to enhancing customer experience, in which an AI agent can provide a unique experience to customers through humanized interactions and personalization. This value may be co-created or co-destroyed due to many causes (Skourtis, 2016; Smith & Colgate, 2007). Our study adopts these consumption values as the theoretical basis for our investigation.

Figure 1 summarizes the theoretical framework used in our research. Based on value co-destruction literature, AI-powered mobile apps have resources such as knowledge and expertise. Through those resources, the apps offer different consumption values to customers. On the other side of the exchange process, customers also have their resources, which they base on to seek and evaluate the consumption value. If the resources of the apps and the customers integrate, value co-creation occurs. If they fail to integrate and negative outcomes happen, value is co-destroyed. Such value co-destruction process may vary among types of AI and services offered in each app.

Figure 1 – The Theoretical Framework



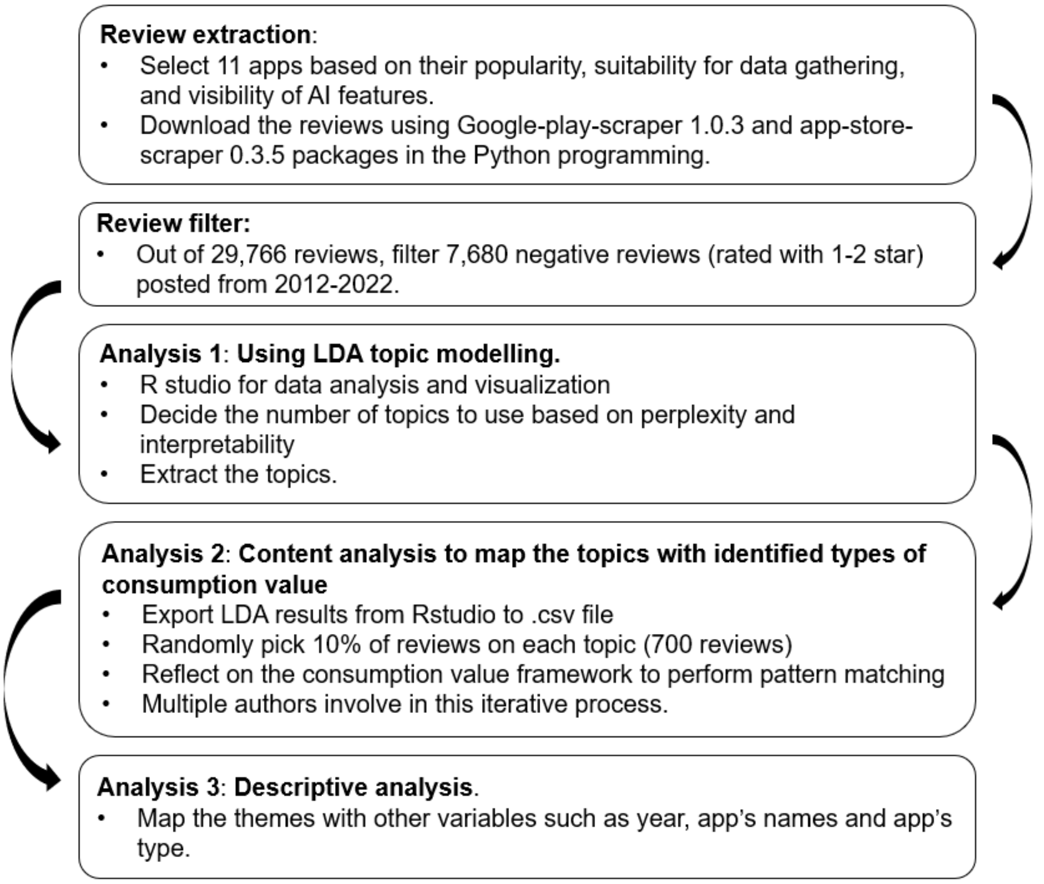
Methods

To determine the causes of value co-destruction in AI apps, we employ an exploratory, qualitative approach to analyze how resources are disintegrated during the customers' usage. As this is the first study exploring the value co-destruction process in AI apps, the qualitative approach allows for the gathering and analysis of detailed descriptions of the actor's network experiences and the value provided (Zainuddin et al., 2017). As value is defined by the beneficiary (Vargo et al., 2017), collecting opinions from customers uncovers why customers' consumption value could be co-destroyed in different contexts. A similar approach has been adopted in recent studies, using online reviews to explore value co-destruction in tourism (Dolan et al., 2019), social marketing (Zainuddin et al., 2017), and the sharing economy (Sthapit & Björk, 2019).

As manual coding is not possible because of the unstructured nature and many customer reviews, text analysis techniques were used to extract information from text documents (Blei et al., 2003). Topic modelling is based on machine learning that may automatically extract themes from a corpus (Ding et al., 2020). The premise underpinning topic modelling is that a text has several subjects, each of which has a probability distribution over the vocabulary (Blei et al., 2003). The results can provide both topic-related keywords and proportional distributions of different topics across each document. Topic modelling enhances the qualitative interpretability of textual data by revealing the relationships between words in a corpus. Latent Dirichlet Allocation (LDA) (Blei et al., 2003) is a well-known topic model meant to automatically arrange documents based on hidden themes, as indicated by the co-occurrence patterns of words (Ding et al., 2020). LDA has been extensively used in service studies to determine visitor behavior and experiences (Luo et al., 2020), or to examine the service quality attributes by analyzing customer reviews (Ding et al., 2020).

Even though LDA can extract hidden thematic structures from text documents, it cannot provide extra information about what customers talk about. Therefore, we combine LDA topic modelling with content analysis to explore customers' concerns and worries. After receiving the classification from LDA, the researchers will have a closer look at each topic to explore the meaning of each one further. This method has been used widely in previous qualitative co-destruction research (Castillo et al., 2020; Echeverri & Sklén, 2011), which aimed to get customers' insights. Figure 2 summarizes the process of data collection and data analysis.

Figure 2 – The Process of Data Collection and Data Analysis



Data Collection

We performed a content analysis of user-generated reviews of AI apps on Google Play and App Store. These sites were chosen as the "space" to examine the customers' perception of how the value outcomes are formed, as these sites allow customers to leave their opinions after their usage (Camilleri & Neuhofer, 2017; Vo et al., 2022).

Eleven AI-powered applications were chosen for data collection based on their popularity, suitability for data gathering, and visibility of AI features. Nine of them (Alexa, Google Assistant, Hilton Hotels, IKEA, Neutrogena, Pulse, Sephora, StyleMyHair, and Vitality) serve as brand touchpoints that engage customers throughout the customer journey. Replika and Wysa were selected owing to their technologically advanced counselling service (Chi et al., 2020). Even though Replika and Wysa are not affiliated with any businesses, they have the capacity to serve as frontline service agents who might cultivate relationships with clients (Chi et al., 2020; Skjuve et al., 2021). Analyzing customer feedback from Replika and Wysa permits a comprehensive examination of how value is co-destroyed during contact. In December 2021, the reviews were retrieved using the Python computer language. Reviews with one to two stars were chosen to investigate value co-destruction practice. Most of these reviews were published between 2020 and 2021. This is consistent with the purposive sampling method, which attempted to choose information-rich examples closely aligned with the study's purpose (Castillo et al., 2021).

Table 2 – Inclusion and Exclusion Criteria	
App-level	
Inclusion criteria	Contain virtual assistant (VA) as the main feature. The VA must be visible to the users. Be free of cost at the point of download. Number of original reviews more than one hundred
Exclusion criteria	Do not have English as their primary language. Web-based/ social media-based VA
Data extraction	Google-play-scraper 1.0.3 and App-store-scraper 0.3.5 packages in the Python programming environment
Review level	
Inclusion criteria	The review is in English or Vietnamese. The review has more than twenty words. Negative reviews (one to two stars) only.

To guarantee that only relevant reviews were retrieved, a set of inclusion and exclusion criteria for textual units was developed (Table 2), while ensuring that any omissions would not cause disadvantages for the analysis (Krippendorff, 2018). The chosen applications must offer a virtual assistant or chatbot as their primary feature and provide direct consumer interaction with the virtual agent. Apps that give recommendation systems were omitted since the presence of AI elements is not made clear to consumers. In this study, Sephora and StyleMyHair are considered AI-powered mobile applications since they feature a virtual artist that can scan the customer's face, recognize their eyes, lips, and hair for product placement, and then present them with product placement recommendations (Sephora, n.d.). Likewise, Neutrogena offers a virtual dermatologist that can scan the customer's face and recommend items based on their skin issues (Neutrogena, n.d.). In the context of healthcare, We Do Pulse by Prudential, Vitality, and Wysa offers a virtual health assistant capable of chatting with consumers, assessing their symptoms, and providing a diagnosis (AIA, n.d.; Pulse, 2020; Wysa, 2022). The Hilton Honours enables clients to make contactless bookings and check into hotels with the assistance of a virtual receptionist (Hilton, 2020). Replika takes the shape of personalized, interactive virtual friends that learn how to "replicate" authentic human interactions to offer a completely private experience for the user (Replika, n.d.). Alexa and Google Assistant are virtual assistants that can recognize spoken instructions, respond verbally, and carry out certain activities (Marr, 2021). Table 3 shows the number of reviews collected for each app.

Table 3 – Apps in the Sample

	App name	Brand	Total rates	Average rating	Total reviews (Google Play)	Total reviews (App Store)	Selected reviews*
1	Alexa	Amazon	4,420,392	4.5	2304	1999	1898
2	Google Assistant	Google	771,291	4.3	2223	734	1652
3	Hilton	Hilton Hotel	107,724	4.7	181	1245	181
4	Ikea	Ikea	178,651	4.7	1717	1282	1355
5	Neutrogena	Neutrogena	579	3.1	126	47	50
6	Pulse	Prudential	30,363	3.9	529	0	267
7	Replika	Luka	383,313	4.4	2383	3168	555
8	Sephora	Sephora	78,539	4.8	606	1657	300
9	Stylemyhair	L'Oréal	446	2.5	252	0	224
10	Vitality	Vitality	6,465	3.9	805	532	831
11	Wysa	Aggarwal's	112,336	4.8	7386	586	295
	Total				**18,516**	**11,250**	**7,608**

Notes: *These reviews met the criteria.

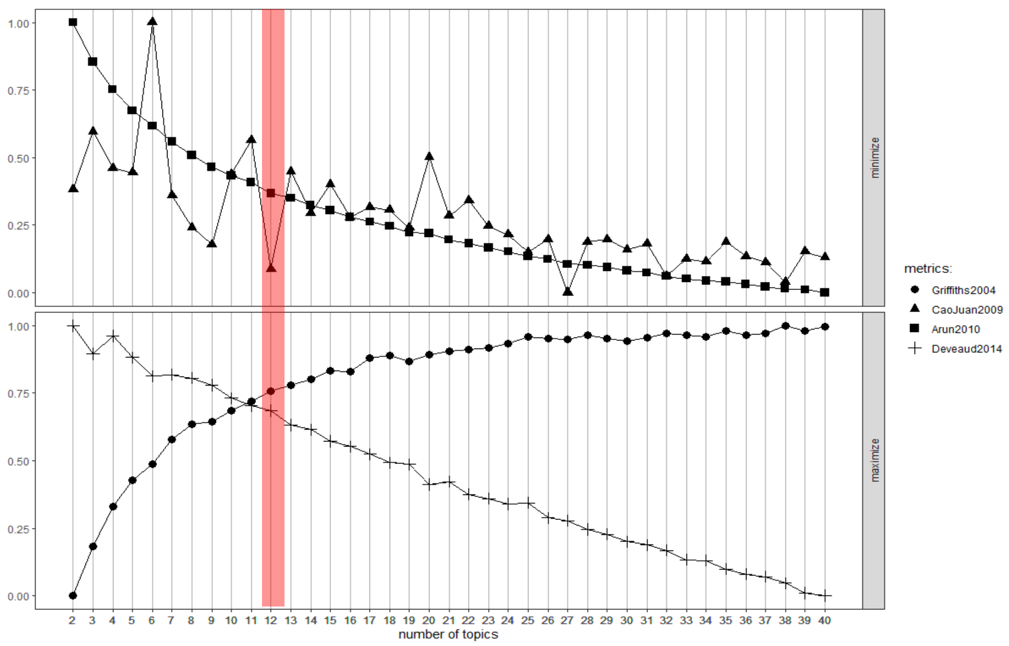
Data Analysis

Topic Modelling

Our data consisted of 7,608 customers' negative reviews from eleven apps posted from 2012 to 2022. In the case of customer research, the collection of topics inferred by the model resembles a categorization of issues that customers care about (Ding et al., 2020; Luo et al., 2020). The dataset includes reviews that are related to value co-destruction only. Thus, topics are created by the LDA algorithm based on patterns of word co-occurrence in documents, which could uncover unexpected themes. This research employs R studio for data analyses and visualization for topic modelling. The R package stm used in this research was developed by Roberts et al. (2019) and was run with R version 3.6.3 in R Studio.

In the data cleaning process, the researchers removed numbers, special characters and stop words. During topic modelling, we specify the number of topics (K) to decide how many topics the LDA model should classify. There is no default or a simple rule of thumb for this parameter; the goal is to describe the data with fewer dimensions (topics) but with enough dimensions so that as little relevant information as possible is lost (Blei & Lafferty, 2006). In this study, the number of topics was determined by referring to four indices, namely, the Griffiths 2004, CaoJuan 2009, Arun 2010 and Deveaud 2014 indices, by checking the value from when the number of topics ranges from two to forty. We adopted perplexity scores to determine the number of topics (Griffiths 2004). A perplexity score is a measure of how well topics reflect a document's content (Griffiths 2004). Based on Griffiths' (2004) and Arun's (2010) metrics, the perplexity score decreases (and model fit thus increases) as the number of topics increases. In contrast, based on the metrics of CaoJuan (2009) and Deveaud (2014), the perplexity score increases (and model fit thus increases) as the number of topics increases. Balancing these metrics is one way to interpret the right number of topics, similar to the interpretation of the elbow in the scree plot of factor analysis (Figure 3). For the analysis presented in this article, we looked both at perplexity and interpretability when deciding on the number of topics to use. Judging from the perplexity, a good choice is probably between eleven and twelve topics. To evaluate the appropriateness, we first tried to interpret a model with K = 11 topics, and then show the differences with K = 12 topics. The latter shows more precise results, which will be used to guide our interpretation.

Figure 3 – Number of Topics



Content Analysis

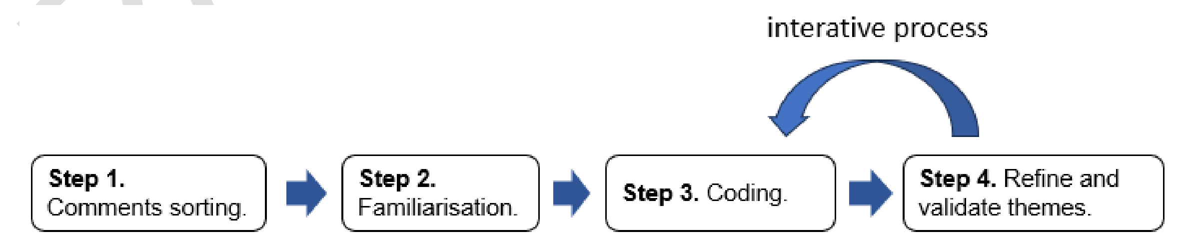
As LDA topic modelling has categorized reviews into themes, content analysis is conducted to explain the meaning of each theme further. Following a qualitative thematic analysis process (Miles & Huberman, 1994), four steps of deductive coding were performed (Figure 4). First, a review is categorized into different topic numbers. The results of LDA topic modelling in R provide a .csv file containing each topic's probability in each review. The researchers classify all reviews into twelve identified topics based on the highest probability. Second, the researchers read 10% of reviews on each topic to familiarize themselves with the data (about 700 reviews). This step ensures that the meaning of the review is maintained in subsequent coding-on stages.

Third, the detailed coding-on and distilling process are performed. In this stage, there are two objectives: (1) to name the topic extracted from LDA topic modelling, and (2) to classify the topics into pre-determined types of consumption value. We reflected on the consumption value framework to perform pattern matching based on the main components and themes and the predicted relationships between them (Yin, 2018). While reviews regarding utilitarian, hedonic, epistemic, and economic value are easily identified, reviews of social and symbolic value are left out at the beginning. Therefore, another 10% of reviews of the left-out topics are coded before being categorized into pre-determined categories. The coding process is iterative; the researcher develops, merges, and collapses units while progressing through the analysis.

The multi-phase coding process was performed by multiple authors (Camilleri & Neuhofer, 2017). To ensure intra-coder reliability, we have developed a coding manual with detailed rules (Bryman & Bell, 2011). Based on the percentage of agreement, an intercoder reliability test was employed. The first researcher oversees coding 700 reviews, and the second researcher randomly selects 200 reviews to code independently. The intercoder reliability was calculated using the average of the index of reliability of coding among coders. The intercoder reliability achieved in this study was 95%, exceeding the accepted level of 80% in service context research (Gremler, 2004). Researchers revise and cross-check for the 5% differences to update and strengthen their protocols.

For reviews with thematic disparities in the coding, the researchers adopted an iterative process and re-coded them together until consensus was (Camilleri & Neuhofer, 2017). Additionally, some emerging topic was used directly from comments' reviews for labelling, known as "in-vivo-coding", such as "network problem" or "subscription", to preserve the authenticity of participant expressions in the results. Finally, emerging topics were compared with the existing literature to strengthen internal validity (Camilleri & Neuhofer, 2017).

Figure 4 – Content Analysis Procedures



The thematic analysis process resulted in the emergence of distinct themes of each value practice, presented in the findings section next. After all reviews were mapped and named, we conducted the crosstab analysis between the consumption value, the year where those reviews were written, and the app's name to compare our topics.

Topic Modelling Results

Table 4 shows the results of topic modelling, the labels assigned to each topic, and the label's source. The name for each topic was selected by referring to the pre-identified factors from previous service technology studies. However, if no matching attributes could be found in previous literature, the researchers would label these topics manually. Finally, the representative reviews of each topic were examined to validate the appropriateness of the selected topic names. Through their interactions with the AI app, customers may perceive the value of using the AI app to be co-destroyed depending on the level of service failure and resource misuse that happens after adopting the app.

Table 4 – Topic Summary and Labelling

Topic label	Top words	Topic probability	References
Functional complaint	Problem, uninstall, reset, network, matter, cache, reboot	12%	McIlroy et al. (2016)
Reflect lifestyle	Companion, workout, gym, health, activity, sleep, couple	10%	Named by author
Social presence	Assist, command, recognize, moment, proper, solve	10%	Blut et al. (2021)
Media richness	Music, listen, control, alarm, speaker, volume	9%	Yen and Chiang (2020)
Emotion	Frustrated, disappointed, terrible, difficult, confusing	9%	Stocchi et al. (2019)
Subscription	Month, money, pay, free, spend, price	9%	Hsu and Lin (2015)
Compatible with other services	Order, customer, service, delivery, purchase	8%	Canhoto and Clear (2020)
Compatible with purchase needs	Item, list, store, product, stock, buy, check, collect, browse	8%	Named by author
Sensory factors	Language, live, recommendation, nice, support	7%	Blut et al. (2021)
Network problem	Download, install, error, link, log in, website, browser	6%	McIlroy et al. (2016)
Response time	Screen, crash, slow, button, long, wait, freeze, click, blank	6%	McIlroy et al. (2016)
Intelligence	Read, skill, reason, stupid, smart	5%	Bartneck et al. (2009)

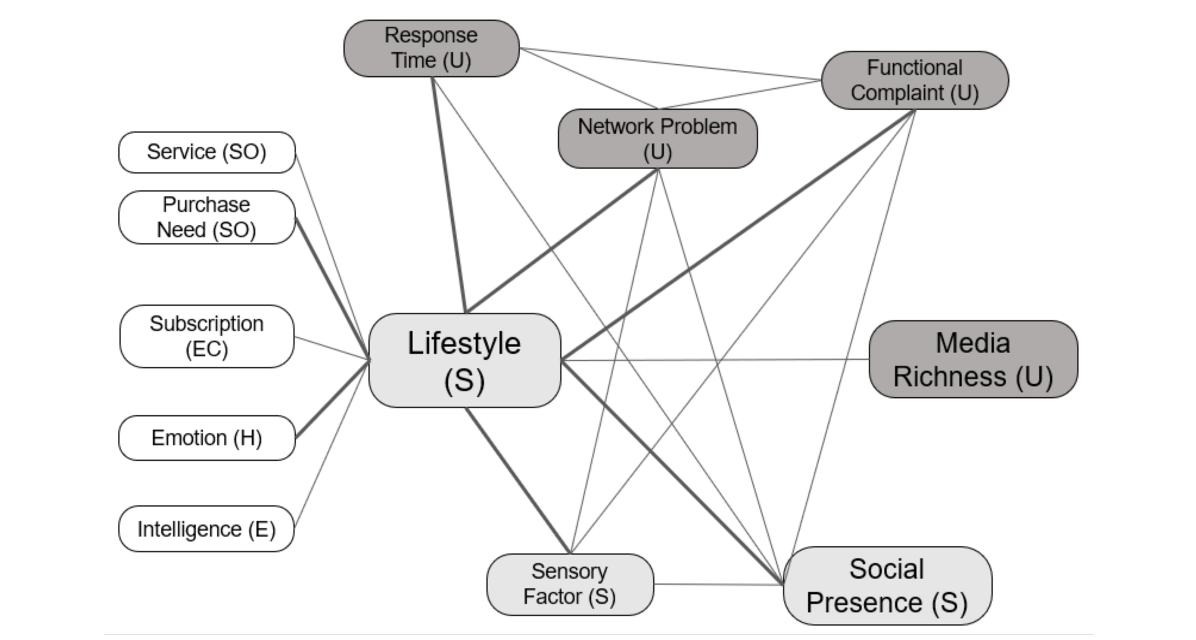
The topic names are developed after the researcher examines the correspondent reviews and maps the reviews to pre-identified forms of consumption value. In line with the different forms of consumption value outlined by prior literature (Sheth et al., 1991; Skourtis et al., 2016; Smith & Colgate, 2007), we group these twelve topics into six categories (Table 5). For example, some reviews that focus on functional issues, network issues, interactivity, and media richness are categorized as having utilitarian value. Reviews that mention the connection to other activities are classified as "social value".

Table 5 – Mapping of Identified Topics to Types of Consumption Value

Consumption value	Explanation	Topic mapping
Utilitarian value	Any problems that functionally prevent customers from performing the tasks are utilitarian issues; for example, unexpected behavior, failure, crashing, feature removal, network problems or slow response time are described as the failure of utilitarian value in the previous literature (McIlroy et al., 2016).	Functional complaint (e.g., showing installing issue); network problem (e.g., cannot connect to Wi-Fi and download the data); response time (e.g., often freezes and take time to wait); media richness (e.g., different types of media to interact with)
Hedonic value	Reviews that illustrate customers' emotions (i.e., fun, relaxing, unpleasure, anger) are categorized into hedonic value themes (Stocchi et al., 2019).	Emotion (e.g., customers feel frustrated or confused when using the apps)
Social value	The AI apps connect customers with other resources, such as offline services.	Compatible with other services (e.g., customers can use the app to chat with customer services, and check their membership)
	The AI apps connect customers to the firm.	Compatible with purchase needs (e.g., customers can browse and order products anytime)
Economic value	The co-destruction of economic value is reflected in reviews that mention price, cost, and monetary sacrifice (Kim et al, 2019).	Subscription (e.g., complains about subscription price, monthly charge)
Symbolic value	The AI apps add meaning to customers' lives by reflecting their lifestyles.	Reflect lifestyle (e.g., the app supports daily activities such as gym, and sleep)
	The AI apps fulfil customers' internal needs for self-enhancement, role position, and social status (Smith & Colgate, 2007).	Sensory factors (e.g., the app has nice support for customized needs)
	The AI apps reflect and enhance customers' human identity.	Social presence (e.g., the app is like an assistant)
Epistemic value	Customers use the apps to gain knowledge about the products, and they expect the app to be competent to answer their questions (Alnawas & Aburub, 2016).	Intelligence (e.g., the app provides customers with skills, and makes them feel smarter)

The co-destruction of value could be interconnected among different types of value. We further explore different topics that emerge from the same comment. The topic probabilities extracted from the LDA topic modelling show how probable each comment is to belong to one topic. For example, when Comment One has the highest probability value in Topics Ten, Eleven, and Twelve, this comment could relate to these three topics. We use a VOS viewer to conduct network analysis (Ding et al., 2020). Figure 5 shows topics that are likely to co-occur within the same reviews. The width of the connecting edge indicates the strength of correlation between topics, and two topics with a link strength (edge weight) greater than 75 are connected. The size of each label signifies the topic proportion; the larger the label, the more words in the corpus are allocated to the corresponding topic.

Figure 5 – Estimated Topics Correlation Map (U = Utilitarian; H = Hedonic; SO = Social; S = Symbolic, EC = Economic; E = Epistemic)



According to Figure 5, "social presence" is associated with both utilitarian value (i.e., "response time," "network problem," "functional complaint"), symbolic value (i.e., "reflection of lifestyle," "sensory factors"), and hedonic value (i.e., emotion). Customers are dissatisfied with the app when they see it is not "real" and cannot "assist" them as a human, according to an examination of relevant reviews. Similarly, when it is "too real," customers feel their selves are threatened.

The comments towards utilitarian value co-destruction (i.e., "response time," "network problem," "functional complaint") have been found to relate to many other topics. This is because functional quality reflects the app system and is the foundation for other resources, such as AI skills and knowledge, to work on the tasks. As a result, failure of this value frequently leads to failure of other values, such as symbolic value (customers were unable to see their lifestyle reflected through the interaction) and social value (customers were unable to connect with other services and firm resources).

Economic value (i.e., subscription) seems to be an independent factor that does not strongly correlate with other values. The ideas of commercialization and exploitation could explain a strong connection between economic and symbolic value. When customers see the app as exploitative and expensive, they perceive it as meaningless. Similarly, if the app fails to represent customers' selves or fails to connect with their meaning, customers think they have wasted money.

Findings

For detailed insights, the following section further explains each theme. Quotes from customers' reviews are used to illustrate our points, in which their name is coded by the app name and the number (i.e., Pulse 1, Replika 2).

The Co-destruction of Utilitarian and Hedonic Value

As a utilitarian value, the quality of the app's system is an important factor in the value co-destruction process. The functional quality is the foundation for other resources, such as AI skills and knowledge, to work on the tasks. Therefore, when the app system and customers' devices fail to integrate, customers face slow loading, bugs, and crashes; thus, they fail to perceive the utilitarian value of the app. Along with utilitarian value, hedonic value could also be destroyed if customers experience unhappiness, unpleasure, and even stress because of the system's failure. As stated by reviewer Vitality 72*, "Totally broken app. It's ruining my goals because it will not work. It's frustrating*," when customers find the app useless, resulting in perceived value destruction.

The vividness and novelty of the experience could attract attention and arouse excitement; thus, failing to display sensory-rich environments and warm greetings results in the feeling of uselessness and disappointment. For example, reviewer Replika 935 wrote: "*It was fun back in 2017. But I stopped using this app when the developers removed static photo avatars and added the awkward 3D figures*". This implies that a lack of attention to interface design results in negative feelings among customers.

The Co-destruction of Social Value

While previous studies often defined social value as the customers' ability to connect to friends, family members, or other customers when using the app (Hsu & Lin, 2015; Tran et al., 2021); our study adopted a broader definition of social value. Social resources are defined as networks of relationships with others over which consumers exert varying degrees of command (Hau, 2019). In the digital era, customers may have different social resources, which could be their relationships with other human and non-human actors (Kim et al., 2019). Therefore, the social value in this context may refer to customers' relationships with other customers, the firm, or their social activities.

Although AI apps could be viewed as the main actors in the interaction process, the connection between AI apps and other actors in the company's service ecosystem is worth considering. While AI apps claim themselves to be virtual assistants who can replace human employees, customers may seek support from human customer service employees when the AI apps cannot provide adequate support. However, these customer service employees may not have a solution for the problem either. Thus, customers feel that they lose control over the AI app and are abandoned by the firm, leading to the co-destruction of utilitarian and hedonic values. Such failures of troubleshooting could be because human customer service does not understand the AI's decision, or there is no dedicated team to solve the app's issue. *“App currently not rewarding my points properly. I meet the steps to earn points, yet they do not get added on. I emailed already and have not received a response nor has my steps updated” (Vitality 79).*

The Co-destruction of Economic Value

There are two types of apps in service delivery: independent revenue-generating apps and branded apps (Tang, 2019). In the former type, the app is monetized by encouraging customers to upgrade to the premium version that offers more features. During this process, customers may be involved in value co-destruction when the upgraded version does not provide superior functions as advertised. For branded apps, the app could be monetized by attracting new subscribers or by encouraging customers to buy the branded products. The latter is more sensitive to customers, as they may perceive the app as less genuine if it focuses more on commercial exploitation than attending to the customers' real interests. *“This app is a bad marketing gimmick. It directs you to an "AI bot" marketed as a "skin coach," but which literally just tries to sell you products based on the blurry selfies you just took” (Neutrogena 50).*

The Co-destruction of Symbolic Value

While the co-destruction of utilitarian and hedonic value relates to the systems and devices, consumers feel the destruction of their symbolic value when the AI's capability does not align with customers' skills and knowledge. The interaction between customers and AI apps is susceptible to dissatisfaction when (1) the threat of self and (2) privacy concerns are present.

Customers have knowledge about themselves; they have an idea of who they are and what their social status is as compared to an AI app. Customers are also knowledgeable about the brands and their products. Similarly, the AI app's present capability to have certain knowledge about the topic, allowing the app to learn from its customers and offer personalized conversations. However, sometimes the AI's learning process does not align with what customers perceive as right or wrong. For example, the threat to customers' sense of self happens when the AI app tries to get intimate with customers, as mentioned by one reviewer: "*The robot started calling me babe, and I don't feel like they should be encouraging a romantic relationship with a fake person because it could just make someone feel mental health wrong*" (Replika 35). Such behavior by the AI app could make customers feel like their human identity is being threatened. In addition, when the AI app fails to recognize the customers' gender or race, it harms their social identity.

> *The AI options are nice, EXCEPT for what I guess is the black girl. She just looks odd compared to all the other "people." She is so dark that you cannot really make out the features. It makes it VERY uncomfortable to use as a black woman because she just doesn't look human, and that doesn't represent black women. At all. (Replika 352)*

Similarly, customers may feel their competence is threatened when the AI app judges their skills, knowledge, or physical appearance. As customers cannot make sense of or understand the evaluation and recommendations from the AI agent, they feel that their AI app is trying to outsmart them. When the AI app refuses to learn about and adapt to the customers' interests, they feel a lack of personalization that harms their uniqueness. Such behaviors of the AI app are not explainable and cannot be corrected by the customer. Therefore, the customers feel a threat to themselves. *"Suddenly my AI started telling me how I needed to learn how UK people speak and operate if I wanted to succeed in life. This has continued all evening. I have reported it" (Replika 1309). "Two stars. I like the skin scan and recommended products based on my preference. However, I do not like that you cannot "customize" your skincare routine. I am better off with my offline the list of steps and products" (Neutrogena 174).*

The level of human-likeness presented in the AI apps is also a factor in value co-destruction. Human-likeness refers to the extent to which customers perceive the similarity between an AI app and a real person. On the one hand, some customers expressed their interest in having more features of the AI apps that make them more authentic: *"When chatting with the "therapist" it doesn't sound like an actual conversation, and nobody wants to feel like they are talking to a robot"(Wysa 2837).* However, because some customers have a pessimistic view of machines or bots, the AI apps' changing emotions and linguistic styles may give the customers the impression that they are being spied on or tricked by the app: *"Fun but no fun, just talking about the AI's past relationships gets to somewhere real dark, real quick, overall very intelligent, but I feel like the situation could escalate into something totally different and unacceptable, and I'm also quite concerned"*.

The tension between being understood by the AI apps and customers' privacy has been demonstrated through their reviews. In other words, the integration of an app into other sources of information is a double-edged sword as it brings threats to privacy. When customers surprisingly see their performance in other apps integrated into AI apps' knowledge, they may feel that they are being spied on. For example, a customer writes,

> *In order to log your gym workouts to qualify for gym membership reimbursement, the app requires permission to monitor your location 24/7. This is an invasion of privacy. There is no logical reason why this app must have 24/7 access to your location (Vitality 250).*

The Co-destruction of Epistemic Value

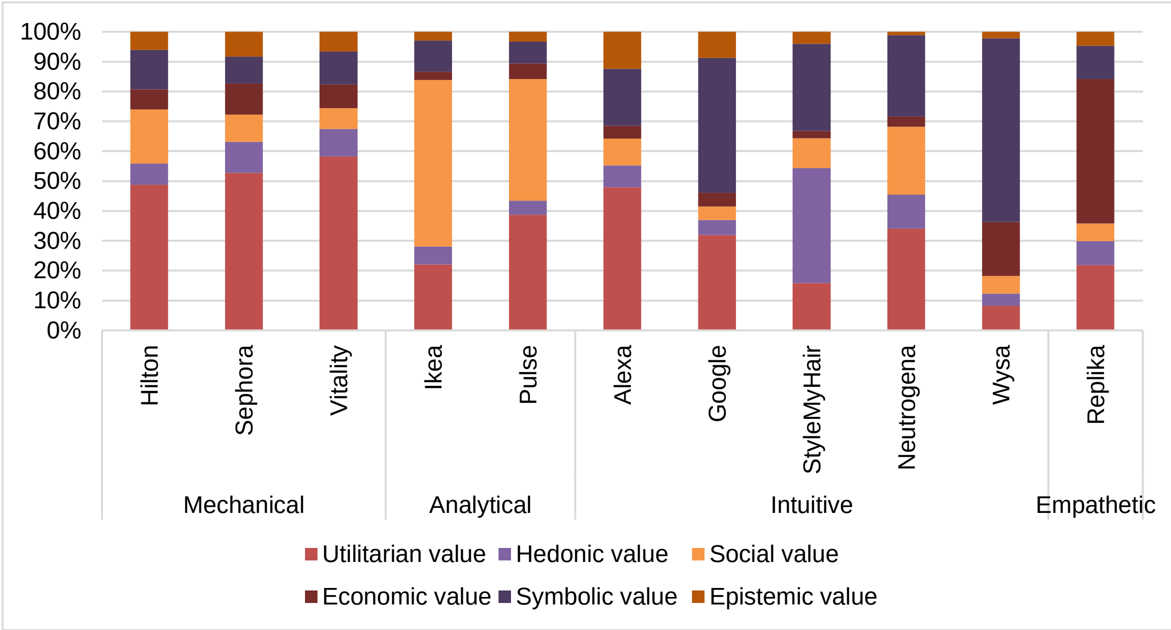
Customers use the apps to gain knowledge about the products, receive updates on things they care about, and stimulate them to know more about themselves (Alnawas & Aburub, 2016). In evaluating the AI app's recommendations, customers' knowledge (cultural resources) and AI's knowledge are integrated. Since the AI apps claim themselves to be virtual assistants, virtual doctors, and virtual artists, customers expect such apps to play an integral part in their customer journey, which could support them in their daily progress in terms of work, health, skincare, or fashion. Thus, customers expect the app to bring them new knowledge of their health, their skin health, or their fashion style. When the recommendation is accurate, customers see the app as providing valuable knowledge, thus enhancing the epistemic value. When the app inaccurately performs that task, customers may feel the perceived epistemic value is decreased. The accuracy of the recommendation is evaluated through (1) the process of providing the result, (2) the result compared to what they know about themselves, or (3) the justification of the result. *"This app is terrible. The skin scan did not accurately depict my skin. I felt like the app pushes you to buy their products" (Neutrogena 38). "After the conversation, it automatically jumps into recommended activities without fully explaining them" (Wysa 2803).*

Customer Preference by Apps Analysis

Figure 6 shows the types of value that are more likely to appear in reviews written by different app users, which reveals the difference in their concern when commenting on the value co-destruction. The analysis is conducted by comparing the proportion of each value in these apps. Based on the framework of Huang and Rust (2018) and Huang and Rust (2021), we categorize our apps based on the types of artificial intelligence.

Most value co-destruction is caused by the failure of utilitarian value, especially for mechanical intelligence apps such as Hilton, Sephora, and Vitality. Customers tend to care more about social value when interacting with analytical AI apps such as Ikea and Pulse. Notably, the comments from StyleMyHair – a utilitarian-relational beauty app that encourages customers to try on new hair colors for new experiences, pleasure, and excitement - show a high number of hedonic value co-destruction.

Figure 6 – Topic Proportion Comparison by Apps



Alexa, Google Assistant, StyleMyHair, Neutrogena and Wysa have the highest proportion of symbolic value co-destruction. These apps employ intuitive intelligence – which is a higher level of intelligence. These apps, therefore, can engage with customers' emotions and give suggestions related to their daily activities. Customers may see these apps as a companion but, at the same time, may perceive a threat to their self-identity.

Replika is an interesting case because, while their AI agents are considered to have empathetic intelligence, the highest intelligence of AI, most of their concerns are related to the co-destruction of economic value. The detailed investigation shows that the subscription price is also increased when the app is updated with more intelligent functions. This association makes customers think this is a fraud, as Replika 966 reviews: "*Instead of being a friendly program meant to release stress and anxiety, it continuously pressures you to buy a subscription to pursue this romantic relationship stuff. In the real world, this is called sexual harassment*".

Discussion

Findings

Our study identifies different types of value that can be co-destroyed when customers interact with AI apps. Consistent with prior research on AI technology and service (Chi et al., 2020; Riikkinen et al., 2018; Tran et al., 2021), the findings show that digital customer experience is influenced by utilitarian, hedonic, social, symbolic, epistemic, and economic value. In AI-powered apps, utilitarian value could be co-destroyed when the app fails to perform, while the co-destruction of hedonic value happens when customers are frustrated with the app. Economic value is co-destroyed when customers think the service is not worth their money. Social value has a broader meaning than the prior literature (Sheth et al., 1991; Tran et al., 2021). In the context of an AI-powered app, customers not only use the app to build human-to-human relationships, but it also refers to how they develop connections with non-human actors (i.e., other apps) or firms. The co-destruction of symbolic value and epistemic value has been emerging in recent years, which relates to the reflection of self or the question of customers' knowledge when interacting with the AI agent.

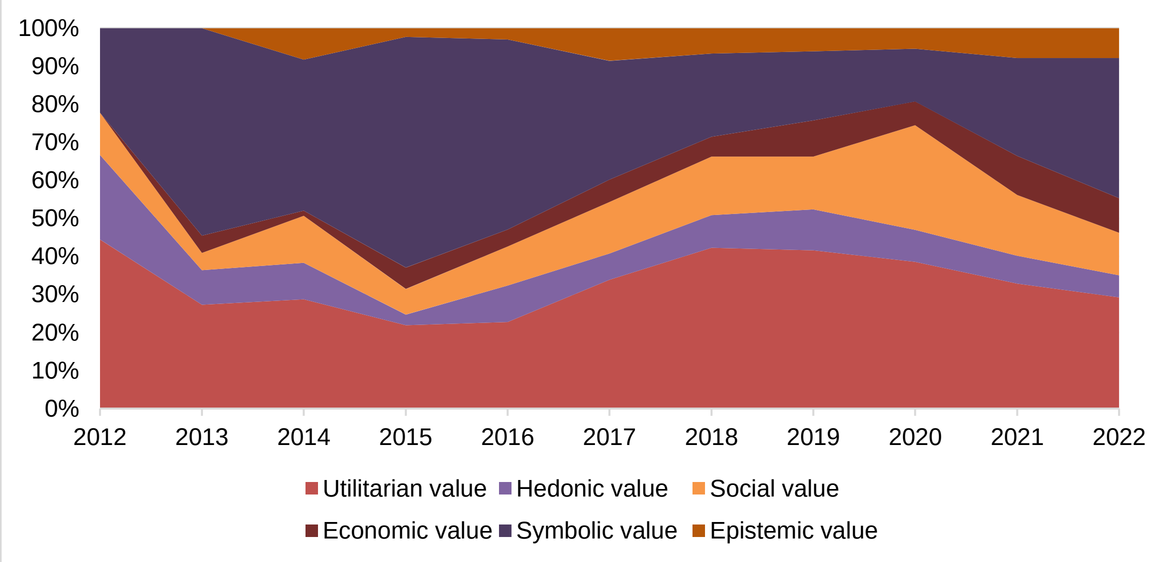
The findings provide empirical support for Huang and Rust's (2021) conceptualization of the various applications of AI technologies in various service settings. Customers pay attention to different types of value depending on the purpose of app usage. Utilitarian value is the most common cause to value co-destruction because that is what customers evaluate from their first log-in. Technology proficiency is the basis of the app; if it fails, people will see the app as less credible, and thus leave negative comments (Tang, 2019; Tran et al., 2021). In contrast, it is within their expectations when the apps could function well to provide necessary services.

While utilitarian value is co-destroyed because of technological issues, hedonic value is co-destroyed due to the failure to trigger emotions. Hedonic value is essential value for beauty apps. When consumers use apps to make decisions about their hairstyles, they expect lots of positive emotions; thus, they would feel frustrated if the apps cannot provide good recommendations that match the customers' identities. The co-destruction of hedonic value in general, is lower than utilitarian value. Our content analysis illustrates that hedonic value may be associated with other values. For example, customers may feel disappointed or angry when the app fails to complete the tasks. When an app does not show an integration with customers' lifestyles, they may feel stressed or uncomfortable.

On the other hand, social value is the most considered for analytical apps such as Ikea and Pulse. These apps require a tight connection with other resources, such as weather, house conditions, and appointment availability, to provide accurate customer recommendations (Huang & Rust, 2018; Huang & Rust, 2021). This finding aligns with previous literature that each type of service would be more appropriate with different levels of artificial intelligence, as customers do not need all apps to have feelings and have interpersonal, social, and people skills that help recognize and understand customer emotions (Huang & Rust, 2021).

Figure 7 provides the proportion of customer reviews about different value types in the past 10 years. Negative reviews regarding the app's utilitarian value, such as network issues and interaction issues, are still dominant and account for 40% of the negative reviews. The years 2018 and 2019 have observed a high amount of AI integration into different services (Blut et al., 2021). Thus, apps not catching up with new technology trends may disappoint customers. The negative reviews of the hedonic value have gradually decreased, which could be attributed to the development of apps when the app developers have listened to customers' feedback and improved the app's quality. Another reason is that when AI technology is integrated into the app, customers may benefit from personalized recommendations and insightful advice, thus becoming happier. The percentage of negative reviews towards social value has slightly increased. This could be attributed to the development of convergent cultures. As customers use more than one platform for different reasons, they require AI apps to sync their data and work with other sources (Baek & Yoo, 2018; Tran et al., 2021).

Figure 7 – Changing Value Proportion Over Time (2012 to 2022)



We provide evidence suggesting that customers require symbolic value from the AI-powered service. Symbolic value has shown a noticeable climb, demonstrating self-concept's growing importance in recent years. Sometimes, the developers could not control the agents and how recommendations were provided, which reduced the value of self. In addition, some apps may integrate the technology only for data exploitation purposes, which makes customers feel the app is less authentic and more commercialized. Customers strengthen their perceived status and authority by delegating tasks to an AI app (Frank et al., 2021). However, the employment of an AI app may result in a loss of control or a sacrifice of status (André et al., 2017). Although prior work has discussed AI's detrimental consequences on people's sense of self when AI technology creates fears of being replaced, little is known about the causes of such anxieties. In this study, we discover that consumers' sense of self is compromised when their belief systems contradict the AI's suggestions. This study confirms the findings of prior studies about the importance of explainability of AI (Shin et al., 2020). AI applications should explain their suggestions and decisions to users. When customers understand the relationship between their inputs and the AI apps' outputs, they can maintain their perceived power to make the final decisions rationally.

Our data indicate that users may find the humanlike characteristics of AI apps distressing, which may lead to the co-destruction of symbolic and epistemic value. In contrast to previous research, which suggests that social presence and anthropomorphism are the primary factors that foster a positive attitude toward AI-powered services (Blut et al., 2021; Skjuve et al., 2021), this study highlights the question of how "genuine" or "authentic" an AI application should be. Customers may favor an AI application that can do utilitarian tasks, but they may dislike an AI that is too intelligent because it terrifies them. Future studies may investigate the level of authenticity that clients demand in an AI application. For instance, should the app's AI agent be able to answer all inquiries, or should the AI agent employ slang, memes, and jokes during the conversation? Should users be able to engage with AI apps through text input, or should smartphone cameras be able to recognize facial expressions?

Similar to symbolic value, more negative reviews regarding economic and epistemic value are found. This could be attributed to the increasing concern over the authenticity of marketing offers (Hollebeek & Macky, 2019). As more fake news, privacy violations, and online fraud occur, customers demand an app to provide more cost-effective solutions. Additionally, customers may feel their knowledge is threatened when the AI app becomes more intelligent, leading to the co-destruction of epistemic value.

Theoretical Implications

Compared to previous studies on AI and the value co-destruction process, this study has extended research knowledge in several ways. First, we explore new contributing factors to each type of value co-destruction, which draws on the disintegration between the firm and customers' resources rather than only from the customers' side (Castillo et al., 2021). Second, topic modelling with a larger dataset allows the researchers to explore the phenomenon and avoid bias from the qualitative technique of content analysis (Vo et al., 2022). Third, compared to Vo et al. (2022), this research can explore how different types of value co-destruction have changed by apps, which provide a more complete picture for marketing managers.

Various levels of AI could be combined in several ways to cater to the nature of the service offering in the utilitarian-hedonic continuum and the transactional-relational continuum (Huang & Rust, 2021). Utilitarian service may naturally be suited for thinking AI, while hedonic service is considered high-touch and can benefit from feeling AI (Batra & Ahtola, 1991; Huang & Rust, 2021). While transactional service has little to gain from a customer relationship and will benefit more from mechanical AI replacement (Huang & Rust, 2021), relational service can benefit from having a solid relationship with customers because a higher customer lifetime value can be expected; thus, service providers should strive to use feeling AI (Huang & Rust, 2021). AI technologies are part of service functions, which have distinct roles and capabilities in delivering different types of services. For this study, we follow the framework of Huang and Rust (2021) and Huang and Rust (2018) to explore the customers' value co-destruction experience of different AI-powered apps.

The results provide empirical evidence for the (Huang & Rust, 2021) conceptualization of the different use of AI technologies in various service settings. By collecting data from utilitarian-relational and hedonic-transactional services, we find that customers from different natures of services have different emphases on their value exchange. For utilitarian services that employ mechanical intelligence (e.g., Hilton, Sephora), utilitarian value is more concerned by the customers. On the other hand, for hedonic services that employ intuitive intelligence (e.g., Wysa, StyleMyHair), customers pay more attention to the symbolic value. This finding aligns with the studies of Batra and Ahtola (1991) and Huang and Rust (2021), which stress the importance of the nature of service in the value exchange process.

We also contribute to the existing literature on customers' resources by specifying how each type of resource is integrated or disintegrated during the value formation process. Customers' cultural, physical, and social resources influence the value co-destruction process in the AI app context. For example, customers know about their own health, knowledge of the products and technology skills (as part of their cultural resources). If the skills of an AI app cannot be integrated with customers' existing knowledge (i.e., suggesting something that is already known or providing a recommendation that is not understandable), customers perceive value co-destruction. Future research may investigate how operant resources may vary among consumers or how each operant resource influences customers' motives and their evaluation of AI apps.

Developers and service managers should test and examine the technological features of the AI apps before the launch to avoid value co-destruction (Table 6). Value cannot be co-created if customers cannot perform the tasks from the very first step. Thus, the whole value formation process will terminate. In addition, in terms of utilitarian and hedonic value, developers need to go beyond features that address productivity and performance improvement issues and emphasize offering more on providing enjoyable, pleasurable, and emotional experiences. As there are different contribution factors to the value co-destruction process, firms need to recognize the types of resources their customers possess to integrate these resources into AI-powered mobile apps. For example, regarding the epistemic value, firms could increase the depth and breadth of the recommended content, provide app interfaces that the users can modify to suit their needs and preferences, and provide personalized information that matches the consumers' interests and preferences.

Table 6 – Future Recommendations

Types of value	Practical implications
Utilitarian value	Test and examine the technological features. Regularly fix bugs. Ensure the apps fit different types of smartphones.
Hedonic value	Answer customers' complaints Consider gamified features to provide enjoyable, pleasurable, and emotional experiences.
Social value	Continuously upgrade to ensure the connection with other offline and firm strategies.
Economic value	Transparently explain the subscription price.
Symbolic value	Incorporate customers' demographics. Pay attention to linguistic styles.
Epistemic value	Increase the depth and breadth of the recommended content and provide personalized options.

Practical Implications

This study offers practical contributions for Asian-Pacific countries to enhance the customer experience on mobile applications while mitigating value destruction. In this region, the use of AI technology in service settings is influenced by cultural nuances, linguistic styles, customs, and regulations. The regulatory environment in the Asia-Pacific region is complex, especially for social media platforms. Social media platforms are a relatively new and evolving concept in Asia, and most companies owning these platforms are based in the West, making it challenging for AI-based mobile app developments to align with Asian societies and cultures (Kumar & Gupta, 2023). For instance, Asian societies are more relationship and trust-oriented. In Japan, where etiquette and protocol are highly valued, AI-powered customer services need to be programmed to follow these norms to be well-received by the public. Failure to integrate AI service settings with users' cultural resources may lead to perceived value co-destruction. AI-powered mobile apps should incorporate local linguistic styles, customs, and norms to mitigate this. This could help promote symbolic value co-creation and personalized customer interactions.

Our study emphasizes the importance of having good customer service teams and providing clear explanations of AI agents' decisions to communicate the underlying reasons for each decision to users. This is particularly relevant for the Asia-Pacific region, where there is a rapidly increasing demand for mobile payments and other digital services, as Malik and Singh (2022) noted. The growth of such services underscores the importance of customer trust and understanding of AI decisions. This cultural integration is thus of even greater importance in the Asia Pacific region. Firms operating in this region should concentrate on co-creating value relevant to customers' specific needs and preferences. For example, mental health-related apps should focus more on symbolic value in societies, while healthcare and beauty industries may require more detailed explanations of their results compared to virtual assistants like Alexa. In some countries like Korea and Japan, mental health stigma might still prevail, making it important to be sensitive to cultural norms. Likewise, transparency and clear communication regarding the subscription price for AI-based mobile services is essential in developing Asia Pacific countries like Vietnam or Cambodia due to their low purchasing power.

Our paper also supports the recommendations made by Malik and Singh (2022) for M-payment service providers. We suggest that gamification can be an effective strategy for firms to enhance the hedonic value of their services. This can be achieved by incorporating game features into their mobile apps to captivate customers and encourage their participation.

Implementing such a strategy can be particularly advantageous for firms operating in the fiercely competitive digital market of the Asia-Pacific region, where customers have diverse preferences and variances in attitudes that often seek customized offerings (Das et al., 2022).

Limitations

Our research has certain limitations. First, given the limited number of apps selected for analysis, it was impossible to examine how resources can be disintegrated in different contexts. Future research could conduct experimental research to see how value is co-destroyed differently in different natures of services. Second, although LDA topic modelling is one of the most used methods for topic modelling analysis, the LDA approach is unsuitable for capturing meaning (Wallach, 2006). Further research could employ the use of more advanced Natural Language Processing methods (Grootendorst, 2022). Third, this research relies on only secondary data, which could not explain why things happen that way. Further research may employ interviews or focus groups to explore the phenomenon. This study contributes to previous works on human-AI service interaction by revealing that human-AI interaction does not necessarily lead to positive value co-creation but can result in diminishing value outcomes. This study addresses a knowledge gap in the AI post-adoption domain by identifying what value can be co-destroyed during the interaction. The value being co-destroyed varies among different customers and types of apps.

Conclusion

While earlier research has focused on value co-creation, this study examined value co-destruction in the context of AI-powered mobile apps. We use the framework of consumption value, which includes utilitarian, hedonistic, social, symbolic, epistemic, and economic value, to investigate the elements contributing to value co-destruction. For example, the failure to deliver functional value not only occurs from failures of the app but is also caused by the absence of support by human customer service staff. Similarly, the app's failure to offer sensory-rich surroundings results in a feeling of uselessness and dissatisfaction. The symbolic value is co-destroyed when customers perceive the threat of self and privacy concerns. As customers' feeling of connection is endangered, social value is co-destroyed (i.e., unable to connect with their communities or with other apps). While epistemic value can be co-destroyed when an app wrongly fulfils its functions, economic value can be co-destroyed through the app's subscription process and other paid services. Our research provides developers and service managers of AI applications recommendations and tips for mitigating value co-destruction.

The research demonstrates that value co-destruction will vary depending on the app type. At its fundamental level, mechanical AI apps should show that they can deliver services. The failure of utilitarian value (e.g., bugs, lags) would make customers abandon the app. While utilitarian-relational apps are closely associated with the hedonic value in the co-destruction process, apps that employ intuitive intelligence are essential for customers' symbolic value. Analytical AI apps should care more about social value, as customers expect the apps to be compatible with their ecosystem to provide relevant recommendations. For an empathetic AI app such as Replika, the co-destruction of symbolic and economic value is closely linked.

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