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Adoption of shopper-facing technologies under social distancing: A conceptualisation and an interplay between task-technology fit and technology trust

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ABSTRACT

As an important measure to combat COVID-19 pandemic, social distancing is observed worldwide and increasingly being regarded as a normative behaviour that guides consumers' daily activities. In response, consumers have embraced a variety of digital technologies that facilitate in-home or contactless shopping. This study examines the emerging presence of technologies in shopping activities under social distancing by: 1) conceptualising the structures of shopper-facing technologies, and 2) examining the interplay between task-technology fit and technology-trust that influences shoppers' adoption of the multi-dimensional technologies. Exploratory factor analysis and structural equation modelling are used for data analysis (n = 508). Our findings reveal three distinctive dimensions of shopper-facing technologies which are labelled as shopper-dominant (pre-) shopping technologies, shopper-dominant post-shopping technologies, and technology-dominant automations. Shoppers' adoption intention depends on their evaluations of the technology fit in performing shopping tasks characterised by contact avoidance/minimisation. The impacts of task-technology fit are further moderated by shoppers' trust in those technologies. More importantly, task-technology fit and technology trust are found to demonstrate differentiated explanatory powers towards shoppers' adoption of the different categories of technologies.

1. Introduction

Following the several waves of health crisis due to COVID-19 virus, the impacts of the pandemic are expected to be long-lasting. As an important measure to combat the virus, social distancing is observed worldwide and increasingly being practised as a new norm that guides consumers' daily activities. As a result, consumers have been adjusting to an 'in-home everything' lifestyle by working, learning and shopping at home (Sheth, 2020). Out of sheer necessity, consumers have embraced a variety of digital technologies that facilitate in-home activities.

In particular, smart shopping and delivery technologies have emerged as the new daily essentials that empower shoppers to search, compare, purchase and receive products anytime and anywhere (Fagerstrøm, Eriksson, & Sigurdsson, 2020; Pantano & Gandini, 2017). Under social distancing, a typical shopping activity would start with searching for recommendations/reviews on social media, followed by placing orders on mobile commerce platforms and requesting for contactless deliveries (e.g. via click-and-collect or self-collect locker). As such, the ubiquitous shopper-facing technologies have brought virtual stores to the consumers' homes, which remove the time and space restrictions inherent to traditional retailers on the one hand (Inman & Nikolova, 2017; Vannucci & Pantano, 2019), and eliminate all unnecessary social contacts during shopping on the other hand.

To this end, shopping, which is primarily a social activity, seems to have become a technology-dependent task for modern shoppers. As suggested by some scholars, modern shoppers now become socially-excluded but technologically-empowered (Dennis, Bourlakis, Alamanos, Papagiannidis, & Brakus, 2017; Papagiannidis, Bourlakis, Alamanos, & Dennis, 2017). Indeed, the transfer from a 'high-touch' to a 'high-tech' orientation has been witnessed in the service industry, which is greatly accelerated by the exceptional situation of the COVID-19 pandemic (Almeida, Duarte Santos, & Augusto Monteiro, 2020; Zeng, Chen, & Lew, 2020). For example, in-store shopper-facing kiosks are

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available for shoppers to check the product information themselves without contacting the sales personnel; Customer service personnel is increasingly being replaced by AI-powered virtual assistants; Automated parcel lockers are being promoted over conventional home deliveries in the field of e-commerce logistics. To an extreme extent, the prolonged practice of social distancing may make the technology-based shopping a common *habit* and the physical shopping a mere outdoor *hobby* in future (Sheth, 2020). In this context, our study aims to examine the emerging presence of technologies in shopping activities.

It is worth pointing out that this study focuses on technology-based shopping behaviours under the special context of social distancing. Such behaviours demonstrate some unique characteristics as follows. Firstly, they are primarily utilitarian-driven as the social elements of shopping are more or less eliminated from the technological context. The experiential shopping behaviours are thus not the focus of this study. To this end, we adopt a utilitarian-centric perspective (e.g. task-technology fit) to explain shoppers' behaviours. Secondly, shoppers initiate the shopping behaviours with a clear short-term functional objective in mind. This is because shoppers are likely to postpone unnecessary shopping in the exceptional situation of social distancing. As a result, they tend to search for relevant information and compare available alternatives that match the anticipated specifications of the products, and subsequently request for post-shopping deliveries. In this regard, this study focuses on the end-to-end shopping process of functional products. Finally, this study does not distinguish between grocery shopping and shopping of general (functional) consumer goods. We argue that shoppers lead a simplified life due to social distancing and they turn to technologies out of necessity. Herein, most shopping activities are motivated similarly, regardless of the types of purchases (e.g. daily groceries or general goods).

Taking an exploratory approach, the *first objective* of this study is to provide an initial conceptualisation of the diverse shopper-facing technologies based on: a) the technologies' functions in the shopping process, and b) the shoppers' dependency levels on the technologies. With the conceptualisation, we further investigate the degree to which the practice of social distancing drives the adoption of different shopper-facing technologies. This is achieved by applying the theoretical insight of task-technology fit (TTF) (Goodhue & Thompson, 1995). More specifically, TTF theory posits that the successful adoption of a technology depends on the fit between the characteristics of the technology and the task where the technology is involved (Goodhue & Thompson, 1995; Zhou, Lu, & Wang, 2010). Accordingly, the *second objective* of this study is to assess the fit of different shopper-facing technologies in performing social-distancing shopping, which ultimately drives technology adoption. In addition, technology trust is often identified as a key concern in human-technology interactions (Ameen, Tarhini, Reppel, & Anand, 2021; Ghazizadeh, Lee, & Boyle, 2012; Lippert & Forman, 2006). It is suggested that the trust concern becomes more prominent when a higher level of dependency is required on technologies (Klumpp, 2017). In line with this school of thoughts, our *third objective* is to examine the interplay between the technology-fit (in this study, task-technology fit and technology-fit are used interchangeably) and technology-trust in shoppers' responses to various technologies. Of particular interest to this study, we aim to discern the differentiated moderating impacts of technology trust on shoppers' adoption of technologies with varied levels of dependency.

This study contributes to the literature by providing a unified conceptual framework of shopper-facing technologies, which are often examined in the scattered literature of retailing, logistics, and e-commerce studies. Furthermore, our work is among the pioneer studies that look into the phenomenon of technology-dependency among modern shoppers which coincides with the current trend of social distancing. In this regard, our study contributes to the literature with an empirically validated model on shoppers' adoption of shopper-facing technologies given the impacts of social distancing. More importantly, we recognise the differentiated impacts of technology-fit and technology-trust on shoppers' adoption of different technologies. Thus, our contribution also lies in a decomposition of the interplay between technology-fit and technology-trust that explains shoppers' mixed feeling of reliance on, and resistance to, technologies in the context of social distancing.

The remainder of this paper is structured as follows. Firstly, a literature review on shopper-facing technologies and theories concerning technology adoption are provided in section 2. Subsequently, two related works of this study are presented. The first work (Section 3) conceptualises and validates the framework of shopper-facing technologies (addressing the first objective), and the second work (Section 4) extends the findings to examine the interplay between technology-fit and technology-trust in shoppers' adoption of different technologies (addressing the second and third objectives). Finally, we conclude this research with theoretical and practical implications.

2. Literature review

Technologies are an important component in creating modern shopping experiences. Various technologies have been examined, which are collectively referred to as shopper-facing technologies (Inman & Nikolova, 2017; Piotrowicz & Cuthbertson, 2014; Vannucci & Pantano, 2019). For example, Voropanova (2015) and Park, Jun, and Lee (2015) explored the use of mobile commerce which created a feeling of being 'smart' among shoppers as empowered by smart technologies. Related to mobile technologies, location-based service technologies, which are a critical tool in creating seamless shopping, have been a recurring theme in omni-channel studies (Yrjölä, Saarijärvi, & Nummela, 2018; YumurtacıHüseyinoğlu, Galipoğlu, & Kotzab, 2017). Bertacchini, Bilotta, and Pantano (2017) provided a more futuristic vision as to how robotic assistants could serve as shopping companions in retail settings. Focusing on the post-shopping stage, Wang, Wong, Teo, Yuen, and Li (2019) and Yuen, Wang, Ma, and Wong (2019) examined the impact of automated parcel stations or smart lockers on creating convenient e-commerce deliveries based on self-collection. Essentially, these are technologies that interact directly with end-shoppers which facilitate end-to-end shopping activities from pre-shopping information search to post-shopping product collection/return.

2.1. *Creating end-to-end shopping experiences: the forgotten element of post-shopping technologies*

While shopper-facing technologies are no recent phenomenon, research in this regard has been conducted in a piecemeal manner scattered in the fields of e-commerce, omni-channel retailing, last-mile delivery and service innovations in general. Importantly, shoppers' participation in post-shopping delivery/collection activities are an integrated part in creating shopping experiences (Wang, Yuen, Wong, & Teo, 2019), especially in the context of e-commerce and omni-channel retailing (Hübner, Kuhn, & Wollenburg, 2016; Wollenburg, Hübner, Kuhn, & Trautrims, 2018). Yet, post-shopping technologies are often ignored by the conventional retailing literature and only briefly examined in the logistics literature.

Logistics researchers have stressed the rising presence of post-shopping technologies in the context of e-commerce deliveries, last-mile logistics and omni-channel retailing (Lim, Jin, & Srai, 2018; Mangiaracina, Perego, Seghezzi, & Tumino, 2019; Murfield, Boone, Rutner, & Thomas, 2017). Within these studies, a consensus has been reached suggesting that the post-shopping delivery service matters in shaping the overall shopping experiences. In fact, it is often identified as one of the most important considerations that influences online shoppers' satisfaction (DHL, 2015; Lim et al., 2018; Vakulenko, Shams, Hellström, & Hjort, 2019). More importantly, empowered with various post-shopping technologies, shoppers are now taking control of when and how to receive their purchases according to their preferences. While the conventional shopping experiences end with final payments, the post-shopping technologies extend the experiences and the associated excitement until the purchases are received and consumed.

Furthermore, in the context of social distancing, the post-shopping technologies become especially essential in facilitating in-home shopping and contactless delivery. Given the restrictions related to physical shopping settings due to COVID-19, shoppers increasingly depend on e-commerce platforms, which makes the post-shopping technologies an indispensable component that is naturally attached to the core shopping process. As revealed by a recent study on shoppers' participation in post-shopping deliveries (Wang, Wong, Li, & Yuen, 2021), a harmonious delivery may greatly enhance shoppers' perception of the overall shopping experiences, whereas a failed delivery may cause value destruction, not only affecting the delivery operators, but also the up-stream retailers and e-commerce platforms. Therefore, it is important to integrate the post-shopping activities in creating end-to-end shopping experiences. To this end, the post-shopping technologies deserve special attention when the shopper-facing technologies are concerned.

Thus, there lacks a unified framework that systematically organises the diverse shopper-facing technologies according to the innate characteristics of the technologies and the associated service stages. Such a framework is critical in providing insights on shopper-technology interactions. To overcome this gap, we propose and validate an initial conceptual framework of shopper-facing technologies based on a literature synthesis followed by an exploratory factor analysis (see Section 3).

2.2. Theoretical insights of technology adoption: technology fit and technology trust

Regarding shoppers' adoption of technologies, a vast pool of theoretical models has been proposed in different service contexts. Most of these models focus on individual's beliefs and attitudes towards technologies which are posited as key antecedent factors that predict adoption intention/behaviour (Oliveira, Faria, Thomas, & Popovič, 2014; Zhou et al., 2010). Models that follow this stream of philosophy include Theory of Reasoned Action (Fishbein & Ajzen, 1975) and its variation of Theory of Planned Behaviour (Ajzen, 1991), Technology Acceptance Model (Davis, 1989), Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003), and Innovation Diffusion Theory (Rogers, 1983). While these models create rich insights on technology diffusion/acceptance, they do not take specific considerations of the task environment, such as the prevalence of social distancing. To this end, the task-technology fit model stands out as a more fitting framework applicable to our study (Goodhue, 1998; Goodhue & Thompson, 1995). More specifically, the model assumes instrumental values of technologies so that a positive evaluation of technology will hinge upon a correspondence between the task needs and the technology functionalities (i.e. task-technology fit) (Goodhue, 1998). Herein, we adopt the task-technology fit model as a theoretical premise to understand shoppers' adoption of different technologies. Of interest, this study examines the extent that the characteristics of shopper-facing technologies match the shopping needs under social distancing (i.e. task characteristics) that leads to shoppers' technology adoption.

Furthermore, technology-facilitated shopping tasks have some unique features, such as the utilisation of virtual environment and unattended self-services, and the impersonal nature of human-technology interactions. These features render a unique environment where trust is of paramount importance (Grabner-Kräuter, Harridge-March, & Faullant, 2008; Lankton, McKnight, & Thatcher, 2014). It is worth pointing out that the extant literature addresses largely interpersonal trusts (i.e. trust on human, service providers), whereas the impersonal form of trust receives much less research attention (Afshan & Sharif, 2016; Grabner-Kräuter et al., 2008; Lippert & Forman, 2006). To this end, the technology itself, which serves as an enabling tool for shopping activities, has to be incorporated as an object of trust. As individuals increasingly depend more on technologies due to social distancing, building trust in technologies is becoming a critical issue. Indeed, technology trust has often been integrated into the task-technology fit model to explain individual's response to technologies (Afshan & Sharif, 2016; Oliveira et al., 2014; Zhao & Bacao, 2020). Therefore, in line with the technology-trust literature, this study explores the interplay between technology-fit and technology-trust in explaining shoppers' adoption of shopper-facing technologies (see Section 4).

3. A conceptualisation of shopper-facing technologies

In this work, we propose a representative list of shopper-facing technologies that facilitate shopping activities with minimal social contacts. A conceptual framework is established underpinning a 2×3 structure of the technologies. Subsequently, an exploratory factor analysis (EFA) is conducted to validate the conceptual framework, and the latent structure of the shopper-facing technologies is thus modified based on the EFA results. Accordingly, a three-factor framework is confirmed which reveals three distinctive categories of shopper-facing technologies.

3.1. An overview of shopper-facing technologies and a proposed conceptual framework

Due to the diverse functionalities of these technologies, the scattered studies on omni-channel retailing, e-commerce and last-mile deliveries are referred and synthesised. The following technologies are identified, which are arranged in an alphabetical order:

- Automated parcel locker (Wang, Yuen, Wong, & Teo, 2018)
- Click-collect (Murfield et al., 2017)
- Crowd-based delivery (Castillo, Bell, Rose, & Rodrigues, 2018)
- Drone delivery (Ramadan, Farah, & Mrad, 2017)
- Interactive search query (Ortlinghaus & Zielke, 2019)
- Location-based marketing (Ryu & Park, 2020)
- Mobile commerce (Voropanova, 2015)
- Real-time track and trace (DHL, 2015)
- Robotic shopping assistant (Bertacchini et al., 2017)
- Social media commerce (Liang & Turban, 2014)
- Text-based chatbot (Adam, Wessel, & Benlian, 2020)
- Virtual reality tool (Caboni & Hagberg, 2019)
- Virtual salesperson (e.g. Amazon Alexa) (Farah & Ramadan, 2020)

To examine the latent structure of these diversified technologies, they are firstly categorised according to their functions, that is.

a) (pre-)shopping technologies which are used for product search, compare and purchase, and
b) post-shopping technologies which are involved in parcel tracking, delivery and collection.

Furthermore, this work adopts the analytical model of human-technology/artificial intelligence collaboration, which differentiates three levels of technology dependency by consumers (Klumpp, 2017). With an increasing level of dependency (and thus personal intrusion), technologies are categorised as follows:

a) Competency-based technologies: these are technologies that provide passive competencies such as information search and parcel storage, whereas consumers retain a full control of the decision-making process.
b) Decision-based technologies: these are technologies that take a part in consumers' decision making by providing suggestions and alternatives based on consumers' input.
c) Automation-based technologies: these are technologies that function with full autonomy and make decisions for human based on their built-in artificial intelligence.

A summary of the conceptual framework is provided in Table 1. Regarding the pre-shopping technologies, a typical example is the **virtual reality technology** that enhances shoppers' sensory by allowing them to 'feel' and try the products remotely in an virtual reality setting (Caboni & Hagberg, 2019). This technology is widely adopted by fashion industry such as apparel, accessories and cosmetics (Beck & Crié, 2018; Lee, Xu, & Li, 2020; Lee, Xu, & Porterfield, 2020). When using this technology, shoppers take the fitting results into consideration whereas the decision whether to purchase the products or not is still within the full control of the shoppers. Thus, the virtual reality technology is categorised as a competency-based technology.

Other examples of pre-shopping technologies include **interactive search query systems** and **chatbots**, both of which are used to answer shoppers' text queries real time. The search query systems are equipped with some basic functionalities such as product availability check and reservation (Ortlinghaus & Zielke, 2019), whereas the interactive chatbots are designed to 'chat' with shoppers using natural language in a similar way to a customer service personnel (Adam et al., 2020; Kasilingam, 2020). Shoppers rely on the competency of the query systems to provide accurate and updated information, while the chatbots engage conversations with shoppers to influence their purchase decision. Given the differentiated depths of human-technology interactions, we propose the search query systems as a competency-based technology, and the chatbots as a decision-based technology.

Regarding the shopping technologies, perhaps the most widely used application is **mobile commerce**. It allows shoppers to search, compare, purchase and return products from their fingertips. The flexibility of the mobile devices enhances shoppers' shopping productivity leading to monetary and non-monetary benefits (Park et al., 2015; Voropanova, 2015). It is found that shopping with a smartphone often associates with a smart-shopper feeling in terms of time/effort saving and utilitarian/hedonic value creation (Fagerstrøm et al., 2020). More recently, a hybrid model of social media and mobile commerce platforms, or **social media commerce** is also gaining popularity among young consumers (Lin, Wang, & Hajli, 2019; Piotrowicz & Cuthbertson, 2014; YumurtacıHüseyinoğlu et al., 2017). It provides accurate recommendations on products or services that match shoppers' interests, habits and lifestyles by analysing the associated social media contents (Liang & Turban, 2014). Furthermore, the social media commerce often incorporates **location-based marketing tools** that push promotional information to shoppers within the targeted geographic areas (Ryu & Park, 2020). Collectively, the SO-LO-MO (social, location-based, mobile) technologies create ubiquitous shopping experiences for consumers (YumurtacıHüseyinoğlu et al., 2017). However, the subtle differences between mobile, social and location-based commerce platforms have to be acknowledged. To illustrate, mobile commerce only passively responds to shoppers' keyword searches (i.e. fulfilling needs), whereas social and location-based retailing tools actively extract and analyse shoppers' behaviour patterns in order to stimulate purchase intention (i.e. creating wants). Considering the different roles played by these technologies in consumers' purchasing decisions, we categorise mobile commerce as a competency-based technology, and social media and location-based commerce as decision-based technologies.

Table 1
Conceptual framework of shopper-facing technologies.

Level of dependency	(Pre-)shopping technologies	Post-shopping technologies
Competency-based technology	• T1: Mobile commerce • T2: Virtual reality tool • T3: Search query (product reservation and availability check)	• T9: Real-time track and trace • T10: Click-collect • T11: Automated parcel locker
Decision-based technology	• T4: Social media commerce • T5: Location-based marketing • T6: Interactive chatbot	• T12: Crowd-based delivery
Automation-based technology	• T7: Virtual salesperson (e.g. Amazon Alexa) • T8: Robotic shopping assistant	• T13: Drone delivery

In addition, the rapid growth of artificial intelligence and robotic technologies have made possible a highly personalised digital shopping experience. Technological applications in this regard include **virtual salesperson** and **robotic shopping assistant** (Bertacchini et al., 2017; Evanschitzky, Iyer, Pillai, Kenning, & Schütte, 2015; Farah & Ramadan, 2020). Different from a chatbot which is essentially a conversational tool, the virtual salesperson and robotic shopping assistant are designed with 'personalities' and cognitive functions (Poushneh, 2021). More specifically, a virtual salesperson such as Amazon Alexa takes a form of humanised voice interface that is capable of problem solving based on active learning (Hildebrand et al., 2020). A robotic shopping assistant goes one step further to provide a personalised companion to shoppers by humanoid social robots (Bertacchini et al., 2017). Given the high level of automation and intelligence incorporated in both technologies, we propose the virtual salesperson and robotic shopping assistant as automation-based technologies.

Regarding the post-shopping technologies, these are a series of logistics applications used in B2C deliveries. For example, after placing orders online, consumers may have the choice to pick up their purchase from their preferred branch store nearby using the **click-collect system** (Murfield et al., 2017). Alternatively, they may self-collect the parcels from **automated parcel lockers** in their neighbourhood upon delivery (Wang, Wong, Teo, Yuen, & Feng, 2020; Wang, Wong, et al., 2019). Shoppers are also able to track their deliveries anytime using the **real-time track and trace tool** which is often provided by e-commerce platforms in collaboration with their logistics partners. These technologies facilitate parcel delivery and collection by providing logistics competencies such as information update, order picking and storage. Thus, they are categorised as competency-based technologies.

Additionally, **crowd-based deliveries** are a recent innovation in e-commerce logistics (Castillo et al., 2018). Via a mobile application or a web-based platform, crowd-based deliveries utilise a many-to-many network to execute small-scale delivery tasks (Castillo et al., 2018; Devari, Nikolaev, & He, 2017). Both parcel senders and receivers are required to share their location information and the crowd platform determines the best candidate (i.e. a registered delivery person) to execute the delivery tasks. The delivery's efficiency and reliability would depend on the technology's inbuilt assignment algorithm and rating system. To this end, shoppers leave the decision on how to execute the parcel delivery to the crowd-based delivery platforms. Therefore, we categorise the crowd-based delivery as a decision-based technology.

Finally, automated delivery technologies are also emerging. **Drone delivery** serves as the most representative example (Kunze, 2016; Ramadan et al., 2017). Drones are unmanned delivery vehicles that are capable of way finding and route optimisation. By using drones, shoppers need to fully entrust their purchases to the technologies' capability of executing safe and gentle deliveries. Thus, drone delivery is conceptualised as an automation-based technology.

3.2. Method

To validate the conceptual framework, a survey instrument was used for this work. A questionnaire was designed to capture shoppers' perceptions towards the proposed shopper-facing technologies. Firstly, the questionnaire started with descriptions on the current practices of social distancing and the proposed technologies that facilitated shopping activities. The purpose was to brief the survey participants with our research context and help them to develop a personal relatedness to this research. The participants would be able to grasp a quick idea about the technologies even if they did not have in-depth knowledge of certain technologies. As such, the data collected reflect the participants' actual perceptions with at least a basic understanding of the technologies, while a certain level of unfamiliarity is allowed that naturally influences their perceptions. Next, the research objective and confidentiality statements were provided. These were to provide assurance to participants that all data would be anonymised and used only for academic purpose.

In addition, information on respondents' demographics (e.g. age, gender and household income) and shopping behaviours (e.g. online shopping frequency) were collected at the end of this section. Respondents who were under 15 years old were automatically rejected as we assumed that they were not the key decision-maker for shopping activities. Respondents who indicated no recent experience (i.e. within past two months) with any of the shopper-facing technologies were also excluded as we assumed that fresh experiences were necessary to develop meaningful perceptions of these technologies. Of note, we aim to capture consumers' perceptual differences of the technologies in general which reflect their understanding of the technologies' functionalities on the one hand, and their perceived ambiguities associated with certain technologies on the other hand. Thus, we did not restrict the sample to consumers who were familiar with all the proposed shopper-facing technologies, which may be a market segment that is too niche to produce generalisable insights.

The main survey consists of two parts. In part 1, the qualified respondents were asked to rate each of the technologies based on the importance in facilitating contactless shopping under social distancing. A nine-point Likert Scale was used with '1' representing 'least important' and '9' 'most important'. As an attention checker, a test question was included to specifically request the respondent to select '7' for a question. Data that failed the test question suggested inadequate attention paid by the respondent when answering the questionnaire, and they were discarded and excluded from further analysis. Part 2 is designed for the second work of this study, which is discussed in Section 4.2.

A professional survey company, Qualtrics (https://www.qualtrics.com/), was employed for survey administration. An online survey was programmed and the survey invitations were sent to the company's panel respondents for their participation. As a common practice by Qualtrics, two or more partnering panels were blended to ensure the representativeness of the sampling frame. The survey was soft launched for three days and officially commenced thereafter with some minor adjustments based on the feedbacks from the soft launch. A total of 1,698 respondents participated in the survey, of whom 1,190 were disqualified (due to underage or lack of experience with the technologies) or rejected (due to failing the test question). Thus, 508 qualified completes were collected for further analysis. A lump-sum survey fee was paid to Qualtrics which included service charges and respondents' rewards. Table 2 shows the sample profile.

Table 2
Sample profile.

	Frequency	Proportion
Gender		
Male	261	51%
Female	247	49%
Age		
16–24	97	19%
25–34	151	30%
35–44	151	30%
45–54	79	16%
>55	30	6%
Household income (SGD/month)		
<3,999	103	20%
4,000–7,999	179	35%
8,000–11,999	122	24%
12,000–20,000	79	16%
>20,000	25	5%
Online shopping frequency		
A few times/year	87	17%
A few times/month	258	51%
A few times/week	139	27%
Almost everyday	24	5%

3.3. Results

To assess the proposed framework of shopper-facing technologies, an EFA (exploratory factor analysis) was performed based on the method of maximum likelihood extraction and Oblimin rotation with Kaiser Normalisation (Osborne, 2014). A three-factor structure was generated when including factors with eigenvalues greater than one. The three-factor solution was also supported by the scree plot, where a break was shown after the third factor. All items resulted in factor loadings greater than 0.50, except for T6 and T9. In addition, T6 and T9 also produced cross loadings. The initial EFA results are shown in Appendix A.

After removing the problematic items of T6 and T9, another EFA was conducted using the same methods of extraction and rotation. With reference to Table 3, a three-factor solution was again produced. The modified EFA suggested good sample adequacy with Kaiser-Meyer-Olkin (KMO) value of 0.90. Furthermore, all items produced factor loadings greater than 0.50 except for T12. T12 resulted in a factor loading of 0.48 which was slightly below the recommended level of 0.50. However, as no noticeable cross loading was detected for T12, we considered the factor loading of T12 acceptable. In addition, *Cronbach's Alpha* was calculated for each factor, that is, 0.87, 0.82 and 0.80, respectively. The values were above the threshold level of 0.70, indicating adequate reliability of the solution. In terms of the extraction sums of squared loadings, about 70% of the variance was explained by the three-factor structure, which confirmed the model validity. As such, the modified three-factor solution was accepted for further interpretation.

The EFA results point to some interesting patterns of the shopper-facing technologies as perceived by the shoppers. Firstly, shoppers make a clear distinction between shopping-related and delivery-related technologies when the technology dependency level is relatively low. To illustrate, Factor 1 relates exclusively to (pre-)shopping technologies (T1 to T5) whereas post-shopping technologies (T10 to T12) form Factor 2.

Furthermore, for Factors 1 and 2, shoppers perceive no difference between competency- and decision-based technologies. This is probably due to the dominant role played by shoppers when interacting with these two categories of technologies, which leaves an assisting position to the technologies. In other words, when shoppers remain as the key decision makers in human-technology interactions, the difference between a reliance on technology competency and technology decision would be too subtle to be cognitively discerned by shoppers. Thus, Factors 1 and 2 contain both competency- and decision-based technologies.

However, automation-based technologies are perceived as a separate factor (Factor 3) from the previous two categories. Herein, shoppers acknowledge a stronger dependency level on technologies when automation-based technologies are concerned. Yet, for these technologies, shoppers seem to have difficulties in distinguishing their different functions. This may be explained by the high dependency level of

Table 3
Modified result of exploratory factor analysis.

	Factor 1	Factor 2	Factor 3
T1	0.60	−0.14	0.05
T2	0.63	0.07	−0.22
T3	0.88	0.02	0.06
T4	0.73	−0.04	−0.03
T5	0.67	−0.00	−0.15
T10	0.09	−0.72	−0.05
T11	−0.10	−0.95	−0.04
T12	0.16	−0.48	−0.03
T7	0.08	0.01	−0.79
T8	−0.06	−0.03	−0.89
T13	0.06	−0.07	−0.52
Cronbach's Alpha	0.87	0.82	0.80

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalisation.

shoppers on these technologies. As a result, shoppers may feel it is unnecessary to distinguish them according to functions because they can be entrusted with end-to-end responsibilities. Alternatively, it may be due to the lack of real-life experiences with these technologies as these are fairly new innovations that are yet to be fully commercialised in the markets. Thus, shoppers view them as a separate group of disruptive technologies. Regardless of the rationales, two (pre-)shopping (T7 and T8) and one post-shopping (T13) technologies collectively contribute to the formation of Factor 3.

Therefore, the initial conceptual framework of shopper-facing technologies is adjusted based on the EFA results. A three-factor framework is thus proposed (see Fig. 1). Given the characteristics of each factor explained above, we name the three factors as shopper-dominant (pre-) shopping technologies (Factor 1), shopper-dominant post-shopping technologies (Factor 2) and technology-dominant automations (Factor 3).

4. An interplay between task-technology fit and technology trust

In this work, we extend the findings from Section 3 and examine the intertwined impacts of technology-fit and technology-trust on shoppers' adoption of the three categories of technologies. A theoretical model is first proposed which hypothesises the relationships among technology-fit, technology-trust and shoppers' adoption intention (See Fig. 2). Given the established differences among the three technology categories in Section 3, we further propose technology-fit to be a stronger predictor for shopper-dominant technologies (Factors 1 and 2) while technology-trust exerts a more extreme moderating effect on technology-dominant automations (Factor 3). Finally, the model is empirically validated by way of structural equation modelling.

4.1. A proposed conceptual framework

Application of task-technology fit model: According to task-technology fit model, shopper-facing technologies are viewed as tools by shoppers in carrying out a portfolio of shopping tasks ranging from pre-shopping searches to post-shopping collection. Task-technology fit is thus the degree to which the technologies assist a shopper in performing those tasks under social distancing. Thus, task-technology fit should be a key determinant of whether the technologies are believed to be useful, important and advantageous (Goodhue & Thompson, 1995; Zhao & Bacao, 2020), leading to shoppers' adoption of these technologies.

Furthermore, the model maintains that, among other factors, the

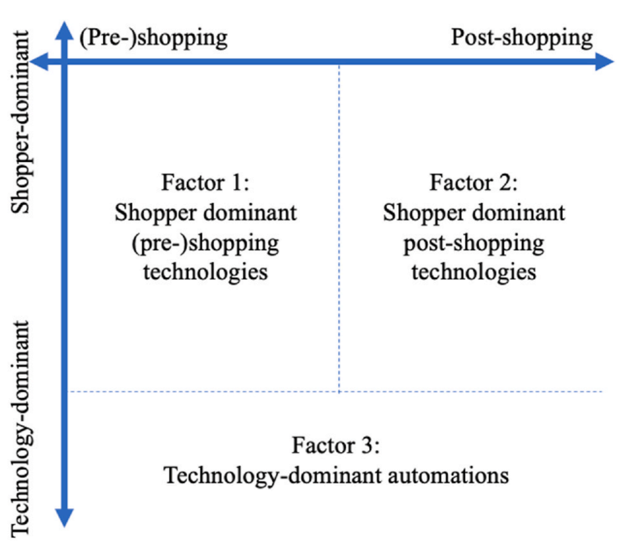

Fig. 1. Modified framework of shopper-facing technologies.

characteristics of the tasks and technologies collectively determine the task-technology fit (Goodhue, 1998; Zhou et al., 2010). For example, a perception of task-technology fit is generated when the task is characterised by a need of secured transaction (e.g. mobile banking) and the technology that builds in a vigorous authentication process (Oliveira et al., 2014; Zhou et al., 2010). Accordingly, in the context of social distancing, the shopping tasks are preferably conducted remotely in home with minimal social contacts. As such, technologies that possess the characteristics which facilitate such a shopping style would lead to a perception of task-technology fit, which ultimately motivates shoppers' adoption of these technologies.

In this work, as to be operationalised in the later section, task characteristics are influenced by the context of social distancing where the shopping tasks are performed. These characteristics may consist of a general desire to follow the stay-at-home recommendation; they may also include specific characteristics such as the needs of avoiding social contacts during the process of shopping and parcel collection. Accordingly, the shopping-facing technologies are designed with 'matching' characteristics. Thus, these characteristics refer to the technologies' capabilities to fulfil the shopping tasks by minimising social contacts or simply by shopping from home. The validity of the task-technology fit model has been repeatedly demonstrated in the context of e-commerce (Liu & Goodhue, 2012), mobile banking (Oliveira et al., 2014; Zhou et al., 2010) and more recently contactless delivery services during COVID-19 pandemic (Zhao & Bacao, 2020). In line with the task-technology fit model, we propose the following hypotheses:

Hypothesis 1. Shoppers' evaluation of task-technology fit is affected by: a) characteristics of shopping tasks, and b) characteristics of shopper-facing technologies.

Hypothesis 2. Shoppers' evaluation of task-technology fit influences their adoption intention of shopper-facing technologies, including: a) shopper-dominant (pre-)shopping technologies, b) shopper-dominant post-shopping technologies, and c) technology-dominant automations.

Application of technology-trust: Compared with the traditional retail setting, shopping activities under social distancing require a higher level of dependence, and hence trust, on technologies. Following the technology trust literature (Lippert & Forman, 2006; Oh, Jeong, Lee, & Warnick, 2013; Zhao & Bacao, 2020), we define technology trust as individuals' belief in the technology's competency in executing related shopping tasks which gives rise to the shoppers' willingness to be vulnerable to and dependent on the technology.

More pertinent to this work, Liu and Goodhue (2012) suggested that a certain level of trust has to be achieved for shoppers to take into serious considerations of other characteristics of the e-commerce setting, such as task-technology fit. To interpret, there seems to be an interplay between technology-fit and technology-trust that determines shoppers' adoption of technologies: when the technology-trust level is low, whether the technology represents a fitting tool to execute the task becomes less an important factor to consider; it is only when the technology is trustworthy enough that the technology-fit becomes a prominent consideration for shoppers. The interplay suggests a moderating effect of technology-trust on the relationship between technology-fit and shopper's adoption intention. More specifically, we expect an enhanced relationship between technology-fit and shoppers' adoption intention given a higher level of technology-trust.

In fact, the lack of trust has been identified as a key factor that explains individual's reluctance to embrace new technologies (Adnan, Md Nordin, bin Bahruddin, & Ali, 2018; Hernández-Ortega, 2011; Lippert & Forman, 2006). It is also positioned as a main hurdle that needs to be overcome to allow meaningful human-and-artificial-intelligence interactions (Klumpp, 2017). Therefore, the following hypothesis is proposed depicting a positive interplay between technology-fit and technology-trust:

Hypothesis 3. With a higher level of technology-trust, the impacts of

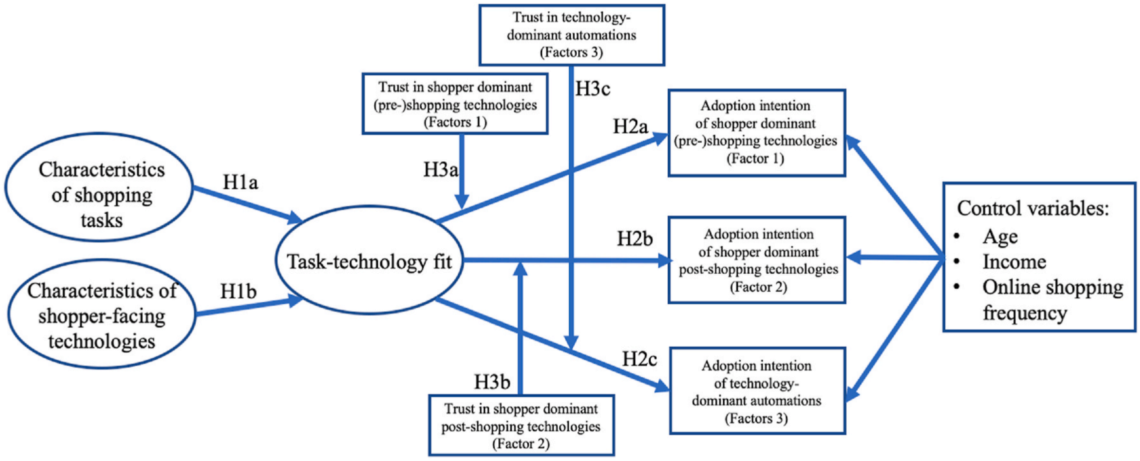

Fig. 2. Structural model illustration.

task-technology fit on shoppers' adoption intention of shopper-facing technologies, including: a) shopper-dominant (pre-)shopping technologies, b) shopper-dominant post-shopping technologies, and c) technology-dominant automations, are strengthened.

In addition, shoppers' demographics and prior experiences are often found to influence their adoption behaviour in general. Thus, shoppers' age, household income and prior online shopping frequency are proposed as control variables.

Differentiated interplay between technology-fit and technology-trust: Given the distinct characteristics of shopper-facing technologies, we foresee the differentiated explanatory powers of technology-fit and technology-trust towards shopper's adoption intention of these three categories of technologies.

According to Klumpp (2017), a higher level of dependency is observed when automations are involved in human-technology interactions. As a result, a higher level of trust hurdle exists for the adoption of automations than the adoption of technologies that only facilitate routine tasks. In other words, technology-trust surfaces as a key concern when technologies are entrusted with full autonomy in the task execution process. It may be further implied that technology-fit represents a prominent consideration only when facilitative technologies are involved, whereas it becomes less a concern when individuals interact with automation-based technologies.

Applying such a rationale, we may integrate the differentiated interplay between technology-fit and technology-trust into our conceptualisation of shopper-facing technologies. More specifically, for shopper-dominant technologies (Factors 1 and 2), shoppers rely on technologies' competencies for decision-making to a limited extent. In that case, we argue that shoppers, as the key decision-maker and shopping-task-executor, emphasise more on the utilitarian perspective of task-technology fit when deciding whether to adopt these technologies.

Similarly, for technology-dominant automations (Factor 3), shoppers allow full autonomy by these technologies in executing shopping tasks, and thus a higher level of trust has to be established before any utilitarian factors (e.g. task-technology fit) are taken into consideration. Consequently, the explanatory power of task-technology fit towards shoppers' adoption of automations is weakened, while the moderating effect of trust in this connection becomes more noticeable.

Hypothesis 4. Shoppers' evaluation of task-technology fit demonstrates stronger explanatory powers (i.e. measured by standard path coefficients and R^2) in predicting the adoption intentions of shopper-dominant technologies (Factors 1 and 2) than predicting the adoption intentions of the technology-dominant automations (Factor 3).

Hypothesis 5. The moderating effect of trust is more extreme on shoppers' adoption intentions of technology-dominant automations (Factor 3) than their adoption intentions of shopper-dominant technologies (Factors 1 and 2).

4.2. *Research method*

The respondents to the part 1 of the survey were directed to participate in the part 2 of the survey. In part 2, respondents were asked to rate the characteristics of the shopping tasks and technologies, the feeling of task-technology fit, and trust in technologies.

More specifically, Measurement items were developed to measure the latent variables in the task-technology fit model, that is, task characteristics (TAS), technology characteristics (TEC) and task-technology fit (FIT). As this work is conducted in the novel context of social distancing, new items were introduced to measure the characteristics of shopping tasks and shopper-facing technologies. With reference to Table 4, TAS was measured by three new scales which characterised the shopping tasks by avoidance of social contact during shopping and parcel delivery (TAS 1 and TAS2), and staying at home as much as

Table 4
Constructs and measurement items.

Constructs and measurement items
Characteristics of shopping and delivery tasks under social distancing (TAS) (Source: developed for this study)
TAS1: I need to receive my parcels without direct contact with delivery person.
TAS2: I need to avoid unnecessary social contact for my daily activities including shopping.
TAS3: I need to shop while staying at home as much as possible.
Characteristics of shopper-facing technologies under social distancing (TEC) (Source: developed for this study)
TEC1: These technologies help me to avoid unnecessary social contact.
TEC2: These technologies help me to comply with social distancing practices.
TEC3: These technologies enable me to stay at home as much as possible.
Task-Technology Fit (FIT) (Source: Zhou et al. (2010))
FIT1: The technologies' functions are sufficient in helping me to complete the shopping and delivery activities.
FIT2: The technologies functions are appropriate in helping me to complete the shopping and delivery activities.
FIT3: In general, the functions of these technologies fully meet my shopping and delivery needs.
*Trust in shopper-facing technologies under social distancing
For your next purchase, to what degree would you trust T1/T2…T13 in providing contactless shopping and delivery services for you in the context of social distancing?
*Adoption intention of shopper-facing technologies under social distancing
For your next purchase, how likely are you going to use T1/T2…T13 if they are readily available?
*Factor analysis results of technology trust and adoption intention can be found in supplementary materials

possible (TAS3). Three new items were also proposed to measure TEC which described the shopper-facing technologies as enabling tools to avoid social contact (TEC1), comply with social distancing (TEC2), and stay at home (TEC3). The construct of task-technology fit was measured by three items adapted from Zhou et al. (2010). These three measures reflected the technologies' sufficiency (FIT1), appropriateness (FIT2) and general suitability (FIT3) in meeting shoppers' shopping and delivery needs. A nine-point Likert Scale was used to rate the measurement items, with '1' for completely disagree to '9' completely agree.

To avoid adding unnecessary complexity to the survey, technology trust and adoption intention were measured by single-item scales. It is a common practice to measure moderators and intention-based endogenous factors using one item especially for complex models (Acheampong & Cugurullo, 2019; Panagiotopoulos & Dimitrakopoulos, 2018; Pavlou & Fygenson, 2006; Yang, 2012). Accordingly, shopper's technology trust on each technology was measured by one item (13 items in total). For each of the shopper-facing technologies, shoppers were asked to rate the degree to which they trust the technology in providing contactless shopping and delivery services in the context of social distancing. The nine-point Likert Scale was again used to capture shoppers' responses, where '1' suggested completely distrust and '9' suggested completely trust. Similarly, shopper's adoption intention of each technology was measured by one item by asking how likely the shoppers were going to use the technology for their next purchase if it was readily available (13 items in total). Their answers were recorded using 1 (highly unlikely) to 9 (highly likely) scales. It should be highlighted that the respondents were informed beforehand about the survey complexity and the amount of incentives paid for qualified completions. They would have accepted the survey invitations only if the incentive level had been acceptable; they were mentally prepared for the survey as to how many questions they were required to answer and the time duration they were expected to be devoted to the survey. Thus, we consider the complexity of survey justifiable given the self-enrolment mechanism and the paid-nature of the study. Summary statistics of trust and adoption intention ratings are provided in Appendix B.

A confirmatory factor analysis was performed to assess the measurement model in the following few steps. Firstly, the model fit indices were evaluated with reference to the recommend acceptance levels (Hair, Black, Babin, Anderson, & Tatham, 2010). For example, the absolute fit indices such as root mean square error of approximation (RMSEA) and standardised root mean square (SRMR) are required to be less than 0.08. Our model results in RMSEA = 0.06 and SRMR = 0.03, both within the accepted level. The relative fit indices, such as comparative fit index (CFI = 0.99), Tucker-Lewis index (TLI = 0.98), incremental fit index (IFI = 0.99) and normed-fit index (NFI = 0.98), are also above the recommended threshold (0.95). Thus, the indices support an overall goodness of fit of the measurement model.

Secondly, the model reliability was assessed. In this step, the composite reliability (CR) and Cronbach's Alpha (CA) were calculated for each construct. As shown in Table 5, all CR and CA values are larger than 0.70, indicating an adequate reliability level of the measurement items.

Table 5
Results of confirmatory factor analysis.

Construct	Measure	Standardised estimate	t-value	AVE	CR	CA
TAS	TAS1	0.85	–	0.67	0.86	0.85
	TAS2	0.90	22.15			
	TAS3	0.70	17.08			
TEC	TEC1	0.85	22.82	0.77	0.91	0.90
	TEC2	0.95	24.79			
	TEC3	0.83	–			
FIT	FIT1	0.81	–	0.72	0.89	0.88
	FIT2	0.89	22.69			
	FIT3	0.85	21.52			

Model fit statistics: $\chi^2 = 61.70$, df = 24, χ^2/df = 2.57, CFI = 0.99, TLI = 0.98, IFI = 0.99, NFI = 0.98, GFI = 0.97, AGFI = 0.95, SRMR = 0.03, RMSEA = 0.06, AVE, average variance extracted; CR, composite reliability; CA, *Cronbach's alpha*

Finally, the convergent and discriminant validities of the model were evaluated. To this end, the average variance extracted (AVE) for each construct was obtained (see Table 5). All AVEs are larger than the recommended reference level of 0.50, which confirms convergent validity of the model. The AVEs were also compared with the squared construct correlations as presented in Table 6. As all the AVEs are larger than the corresponding squared correlations, the model's discriminant validity is also supported.

4.3. Results

Structural model analysis (Hypotheses 1 and 2): Upon confirming the reliability and validity of the measurement model, we can then proceed with the structural model analysis. The analysis results are shown in Fig. 3 and Table 7. The model fit indices confirm a good fit overall of the structural model with the data ($\chi^2 = 246.65$, df = 75, χ^2/df = 3.29, CFI = 0.96, IFI = 0.96, GFI = 0.94, AGFI = 0.90, SRMR = 0.06, RMSEA = 0.07). Furthermore, all the standardised coefficients (β) of proposal structural paths are statistically significant ($P < 0.001$). As hypothesised, characteristics of shopping tasks (β = 0.29***) and shopper-facing technologies (β = 0.58***) collectively lead to a feeling of task-technology fit, supporting hypotheses 1a and 1b. The factor of task-technology fit predicts the adoption of shopper-dominant (pre-) shopping technologies (PRE) (β = 0.59***), shopper-dominant post-shopping technologies (POS) (β = 0.52***) and technology-dominant automations (AUT) (β = 0.34***). Hence, Hypotheses 2a, 2b and 2c are also supported.

Regarding the control variables, age is found to negatively influence the adoption of shopper-dominant (pre-)shopping technologies. It suggests that older shoppers are less likely to adopt such technologies. In addition, more experienced shoppers, that is shoppers who purchase more frequently online, are more likely to adopt technology-based automations. However, compared with the task-technology fit factors, all control variables exert negligible impacts on shoppers' adoption intentions. Appendix C shows the analysis results of the structural model without the control variables.

Moderating effects of technology-trust (Hypothesis 3): Multi-sampling analysis is conducted to validate the moderating effects of technology trust (Vandenberg & Lance, 2000). Prior to conducting the analysis, the sample is split into sub-groups based on the mean scores of technology-trust of three categories of technologies. More specifically, to test the moderating effect of technology-trust on the path of FIT to PRE, the sample is split into a 'High' subgroup (consisting of shoppers who give higher than average ratings regarding their trust on shopper-dominant (pre-)shopping technologies, n = 242) and a 'Low' subgroup (consisting of shoppers who give lower than average ratings regarding their trust on shopper-dominant (pre-)shopping technologies, n = 266). Similarly, the sample is also split based on the mean trust scores of the remaining two categories of technologies. Thus, three pairs of sub-groups are created to test the moderating effects of technology trust on the adoption of three categories of shopper-facing technologies.

The moderating effects are determined by comparing the path

Table 6
AVE, construct correlation and squared correlation.

Constructs	TAS	TEC	FIT
TAS	0.67[a]	0.56[b]	0.59
TEC	0.31[c]	0.77	0.72
FIT	0.35	0.52	0.72

[a] Average variance extracted are along the main diagonal.

[b] Correlations between constructs are above the main diagonal.

[c] Squared correlations between constructs are below the main diagonal.

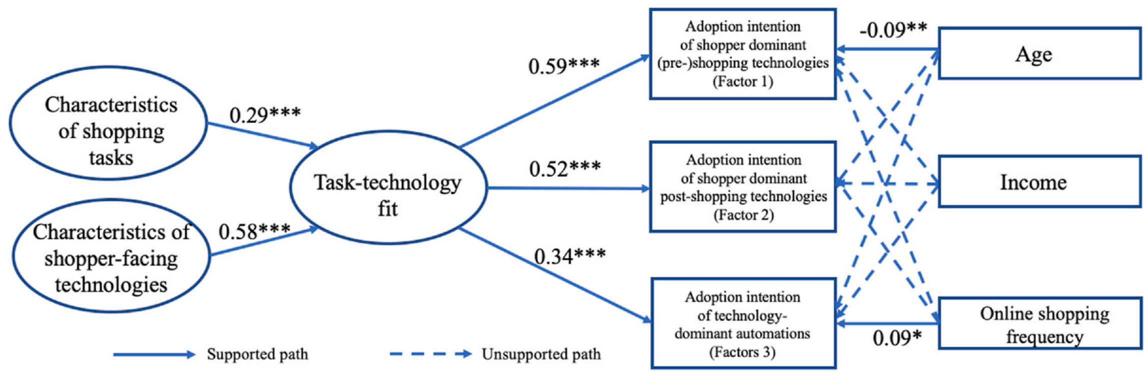

Fig. 3. Hypotheses test results.

Table 7
Hypotheses testing.

Hypothesis	Path	Standardised path coefficient (β)	t-Value	P-Value	Test result
H1a	TAS to FIT	0.29	6.43	***	Supported
H1b	TEC to FIT	0.58	11.63	***	Supported
H2a	FIT to PRE	0.59	13.63	***	Supported
H2b	FIT to POS	0.52	11.97	***	Supported
H2c	FIT to AUT	0.34	7.62	***	Supported
Control variables					
Age [a]	Age to PRE	−0.09	−2.56	**	–
	Age to POS	−0.07	−1.72	>0.05	–
	Age to AUT	−0.06	−1.50	>0.05	–
Income [b]	Income to PRE	0.06	1.51	>0.05	–
	Income to POS	0.04	1.14	>0.05	–
	Income to AUT	0.08	1.88	>0.05	–
Online shopping frequency [c]	Frequency to PRE	0.02	0.59	>0.05	–
	Frequency to POS	0.02	0.60	>0.05	–
	Frequency to AUT	0.09	2.33	*	–

Model fit statistics: $\chi^2 = 246.65$, df = 75, $\chi^2/df = 3.29$, CFI = 0.96, IFI = 0.96, GFI = 0.94, AGFI = 0.90, SRMR = 0.06, RMSEA = 0.07, *P < 0.05, **P < 0.01, ***P < 0.001.

[a] Shoppers' age is coded as a dummy variable with '0' representing younger shoppers (n = 262), '1' representing older shoppers (n = 246).

[b] Shoppers' household income is coded as a dummy variable with '0' representing shoppers with a lower income level (n = 282), '1' representing shoppers with a higher income level (n = 226).

[c] Shoppers' online shopping frequency is coded as a dummy variable with '0' representing infrequent shoppers (n = 345), '1' representing frequent shoppers (n = 163).

constrained and non-constrained models based on the chi-square difference (see Table 8). For example, the FIT-PRE constrained model results in a significant difference as compared to the non-constrained model ($\Delta\ \chi^2 = 4.15$ with one degree of freedom change, P < 0.05). The result suggests that the FIT-PRE path conveys significantly different meanings to shoppers from the two sub-groups. In fact, the path coefficient is significantly higher for shoppers who place a higher level of trust on these technologies (β = 0.46***) than those whose trust level is lower (β = 0.37***). Therefore, the result suggests a positive interaction between technology-trust and technology-fit regarding the adoption of shopper-dominant (pre-)shopping technologies, thus supporting Hypothesis 3a.

However, no empirical evidence is found to support Hypothesis 3b. Comparing the FIT-POS constrained and non-constrained models, no significant difference can be detected based on chi square difference ($\Delta\ \chi^2 = 0.26$ with one degree of freedom change, P > 0.05). The path coefficients for the 'High' (β = 0.37***) and 'Low' (β = 0.35***) sub-groups are also close to each other. Thus, Hypothesis 3b is rejected, which indicates that trust on shopper-dominant post-shopping technologies does not affect shoppers' adoption of these technologies.

Finally, the moderating effect of trust on the path of FIT-AUT is confirmed based on the same test method ($\Delta\ \chi^2 = 10.75$ with one degree of freedom change, P < 0.01). A closer examination on the path coefficients reveals distinct responses to technology-dominant automations when shoppers have different levels of trust on these automations. To elaborate, when the trust level is low, technology-fit becomes an insignificant consideration in shoppers' adoption intention (β = $0.06^{n.s.}$). It is only when these automations are trusted that a feeling of technology-fit would lead to shoppers' adoption of these automations (β = 0.33***). As such, a moderating effect of technology-trust can be detected which is characterised by an extreme enhancement of shoppers' adoption intention of technology-dominant automations due to technology-fit. Hypothesis 3c is thus supported.

Differentiated interplay between technology-fit and technology-trust (Hypotheses 4 and 5): By comparing the magnitude of path coefficients, the factor of task-technology fit seems to be a weaker predictor of AUT (β = 0.34***) than PRE (β = 0.59***) and POS (β = 0.52***). Furthermore, by adding an equality constraint to paths FIT-PRE and FIT-AUT, a significant difference can be detected based on

Table 8
Results of moderating tests.

Hypothesis	Path	Trust level	β	CFI	SRMR	$\Delta\ \chi^2/\Delta df$	Test result
H3a	FIT to PRE	High (n = 242)	0.46***	0.94	0.08	4.15*	Supported
		Low (n = 266)	0.37***				
H3b	FIT to POS	High (n = 267)	0.37***	0.95	0.06	$0.26^{n.s.}$	Not supported
		Low (n = 241)	0.35***				
H3c	FIT to AUT	High (n = 274)	0.33***	0.95	0.08	10.75**	Supported
		Low (n = 234)	$0.06^{n.s.}$				

*P < 0.05, **P < 0.01, ***P < 0.001, n.s. Not significant (P > 0.05).

the chi square change ($\Delta \chi^2 = 13.16$ with one degree of freedom change, $P < 0.001$). Similarly, when the equality constraint is added to paths FIT-POS and FIT-AUT, a significant change in chi square is also detected ($\Delta \chi^2 = 8.21$ with one degree of freedom change, $P < 0.01$). The results suggest that the constrained models are significantly worse as compared with the non-constrained model, indicating a statistical inequality between paths FIT-PRE (FIT-POS) and FIT-AUT. Thus, we can conclude with confidence that the path coefficient of FIT-AUT is statistically smaller than those of FIT-PRE and FIT-POS. The same difference is also reflected by the explanatory power of the task-technology fit model towards shoppers' adoption intentions. In fact, about 35% and 28% of the variances of PRE and POS are explained by the respective model, whereas the model only explains 14% of the variance of AUT. Therefore, our findings indicate a stronger explanatory power of the task-technology fit factor towards shopper-dominant technologies than technology-dominant automations. Thus, Hypothesis 4 is supported.

Regarding Hypothesis 5, Fig. 4 illustrates the differentiated moderating effects of technologies trust based on test results of Hypothesis 3. Positive interactions between technology-trust and technology-fit can be observed on all three paths as indicated by the upward lines with different slopes. However, trust is found to exert the most severe moderating effect on shoppers' adoption of technology-dominant automations (i.e. grey line with the steepest slope), followed by shopper-dominant (pre-)shopping technologies (i.e. blue line with a flatter slope) and shopper-dominant (post)shopping technologies (i.e. orange line with a nearly horizon slope). The illustration is in line with our Hypothesis 5. Herein, we may accept Hypothesis 5 (based on descriptive statistics) which supports a stronger moderating effect of trust towards the adoption of technology-dominant automations than shopper-dominant technologies.

5. Discussion and conclusion

Due to the current practices of social distancing, shoppers increasingly rely on technologies to perform shopping tasks. Against this background, this study proposes and validates a conceptual framework of shopper-facing technologies, based on which the intertwined impacts of technology-fit and technology-trust on shoppers' adoption of technologies are hypothesised and confirmed. The findings of this research make several contributions theoretically and practically.

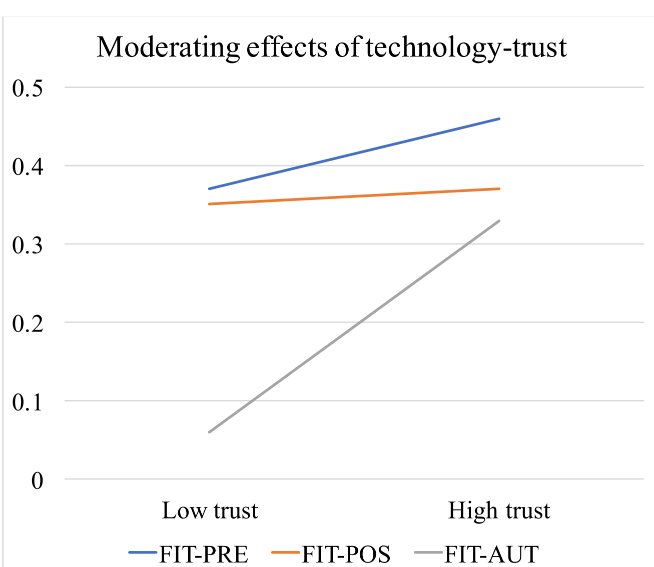

Fig. 4. Illustration of moderating effects of technology-trust.

5.1. Theoretical contribution

A three-factor framework of shopper-facing technologies: This study contributes to the literature with the first theoretical framework of shopper-facing technologies. Compared with previous studies (Inman & Nikolova, 2017; Vannucci & Pantano, 2019), our framework considers the diverse functionalities of the technologies on the one hand (e.g. (pre-)shopping or post-shopping) and differentiates the human-technology interactive patterns on the other hand (e.g. shopper-dominant or technology-dominant). The empirical evidence suggests that a clear distinction between (pre-)shopping and post-shopping technologies is made by the shoppers when they assume a dominant role in the shopping activities. However, such a distinction becomes ambiguous for technologies that are granted with full autonomy in shopper-technology interactions. Thus, the three distinctive dimensions of shopper-facing technologies are identified, labelled as shopper-dominant (pre-)shopping technologies, shopper-dominant post-shopping technologies, and technology-dominant automations. The framework lays the foundation for future research that further explores the rich interactive patterns between shoppers and technologies/artificial intelligences/service robots.

Differentiated explanatory powers of technology-fit on shoppers' adoption intention: This study applies the theoretical insights of task-technology fit to explain shoppers' adoption intention of technologies. We integrate the unique context of social distancing as the characteristics of shopping tasks. In line with the previous task-technology fit literature (Oliveira et al., 2014; Zhao & Bacao, 2020), our study successfully predicts shoppers' adoption intentions based on the level of task-technology fit in addressing shopping needs under social distancing. More importantly, our study extends the existing literature by revealing the differentiated explanatory powers of technology fit on shoppers' adoption intention of different technologies. It is found that technology-fit represents a stronger predictor for the adoption of technologies that depend more on shoppers' inputs and judgements, whereas the explanatory power is weakened when the technologies are incorporated with a high level of automation. To this end, our study also extends the current literature on technology adoption by adding another dimension of consideration on the level of automations. We argue that this dimension is especially critical with the rapid development of artificial intelligence and robotic technologies. Our study provides the initial empirical evidence in this regard, and we expect more research to explore the impact of technological automation on shopper-technology interactions.

Interplay between technology-fit and technology-trust: Given the impersonal natural and virtual environment when using shopper-facing technologies, this study examines moderating effects of technology-trust. Three different types of interactions between technology-fit and technology-trust are detected, suggesting a high level of interaction when technology-dominant automations are concerned, a low level of interaction when (pre-)shopping technologies are concerned, and no interaction when post-shopping technologies are concerned. Thus, this study contributes to the trust literature with a decomposed view of technology-trust as a moderator (Ameen et al., 2021; Ghazizadeh et al., 2012; Lippert & Forman, 2006). Notwithstanding the rich theoretical insights addressing the role played by trust in individuals' adoption of technologies, this study goes one step further by recognising the differences in technologies' functionalities and levels of autonomy, and thus the different roles played by trust.

5.2. Practical implications

Firstly, the three-factor framework provides guidelines to retail managers by pinpointing the three key dimensions of technologies that facilitate contactless participation from shoppers during the special context of social distancing. These technologies, which help shoppers through the difficult period of time, may foster dependency from shoppers which leads to loyalty and satisfaction. As a result, rather than temporary alternatives due to the exceptional situation of the pandemic, the shopper-facing technologies may create long-lasting effects that change shopping habits and introduce new customer relationship management strategies. Thus, our framework serves as a reference to the retailers that guides their investment decisions on shopper-facing technologies.

Secondly, the differentiated impacts of technology-fit on shoppers' adoption allow varied levels of flexibility when implementing shopper-facing technologies. To illustrate, for technologies that merely facilitate shopping activities, more task-specific features should be included to establish a good task-technology fit perception in order to encourage shoppers' adoption. In contrast, for technologies that guide shoppers with full autonomy, task-technology fit becomes a less important factor in shoppers' adoption decision. Thus, shoppers may expect to be surprised by the automations with more unconventional features. In addition, while not hypothesised, the technology-fit is found to better explain shoppers' adoption of (pre-)shopping technologies than the post-shopping technologies. This also implies the potential of incorporating outside-of-the-box features in post-shopping technologies that enable more flexible processes of delivery/collection.

Finally, understanding the different interplays between technology-fit and technology-trust is important for retailers. The difference is probably due to the distinctive trust concerns when shoppers interact with different technologies. For example, shoppers are required to place a high level of trust or even 'blind trust' on automations, whereas a lower level of trust is expected (e.g. payment and revealing private information) when using (pre-)shopping technologies. For post-shopping technologies, trust becomes a least concern as shoppers are mainly engaged with operational activities in this stage. Thus, retailers should prioritise resources accordingly to cater shoppers' trust concerns with different technologies. To illustrate, shopper-facing technologies with automations may be incorporated with more flexible features, but a higher level of trust is required for shoppers' adoption. Comparing (pre-) shopping and post-shopping technologies, the formal ones may be prioritised when investing resources in protecting shoppers' privacy and financial transaction security.

5.3. Limitations

Some limitations of this research need to be acknowledged. Firstly, the study was conducted in Singapore when a 'lockdown' measure was in place (from April 7 to June 18, 2020). During this period, people were encouraged to stay indoor as much as possible and penalties might be incurred if going out for unessential activities. Singapore is also known for its effective enforcement of regulations based on heavy fines. Thus, the lockdown measure influences shoppers' perceptions on shopper-facing technologies, that is, shoppers may rely heavily on these technologies and thus place a high value on them in order to comply with the recommended social distancing measures. Interpretations of our findings should consider the contextual environment (e.g. lockdown measures and the associated enforcement level) where this study was conducted.

Furthermore, due to limited applications of automations in shopper-facing technologies, shoppers' experiences with these technologies are restricted. The unfamiliarity might explain the emergence of technology-based automations as a separate dimension of shopper-facing technologies. However, the situation may change as more related applications are commercialised in the near future. Hence, our proposed three-factor framework may be subject to changes as shoppers become more familiarised with technologies, such as robotic shopping assistant and drone delivery. We encourage future researchers to adjust and modify our framework while considering up-to-date development of shopper-facing technologies.

Finally, this study characterises technology-based shopping behaviour as utilitarian-driven and being initiated due to immediate needs of functional goods. While these are rational assumptions given the context of social distancing, they may over-simplify the actual shopping motivations. For example, research has shown that some shoppers participate in virtual brand communities (Giovanis & Athanasopoulou, 2018; Snyder & Newman, 2019), and the technology-based shopping behaviours are thus motivated by experiential considerations. Thus, our findings should only be interpreted in light of the proposed assumptions.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2021.106900.

Appendix A. Initial EFA results

	Factor 1	Factor 2	Factor 3
T3	0.87	−0.01	0.07
T4	0.72	0.04	−0.03
T5	0.70	−0.01	−0.15
T2	0.61	−0.05	−0.21
T1	0.59	0.15	0.05
T9	0.32	0.31	−0.10
T11	−0.10	0.91	−0.05
T10	0.05	0.77	−0.04
T12	0.24	0.51	−0.01
T8	−0.08	0.03	−0.90
T7	0.09	−0.00	−0.78
T13	0.05	0.08	−0.51
T6	0.43	0.01	−0.46

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalisation.

Appendix B. Average trust and adoption intention

		Trust	Adoption intention
Shopper-dominant (Pre-)shopping technologies	T1	6.90	6.92
	T2	5.78	5.79
	T3	6.35	6.34
	T4	6.06	5.98
	T5	6.11	6.13
	Mean (S.D.)	6.24 (±1.27)	6.23 (±1.43)
Shopper-dominant Post-shopping technologies	T10	6.65	6.43
	T11	6.67	6.40
	T12	6.24	6.23
	Mean (S.D.)	6.51(±1.32)	6.35 (±1.58)
Technology-dominant Automations	T7	5.76	5.62
	T8	5.62	5.53
	T13	5.59	5.38
	Mean (S.D.)	5.66 (±1.47)	5.51 (±1.79)

Appendix C. Structural model without control variables

Hypothesis	Path	Standardised path coefficient (β)	t-Value	P-Value	Test result
H1a	TAS to FIT	0.29	6.45	***	Supported
H1b	TEC to FIT	0.58	11.63	***	Supported
H2a	FIT to PRE	0.59	13.57	***	Supported
H2b	FIT to POS	0.53	11.95	***	Supported
H2c	FIT to AUT	0.35	7.59	***	Supported

Model fit statistics: $\chi^2 = 227.12$, df = 48, CFI = 0.95, IFI = 0.96, GFI = 0.93, AGFI = 0.89, SRMR = 0.07, RMSEA = 0.07, ***$P < 0.001$.

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Credit author statement

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