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Brand competitiveness and resilience to exogenous shock: Usage of smartphone apps during the COVID-19 pandemic

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ABSTRACT

This study examines the factors that affect brand competitiveness in an environment of uncertainty caused by exogenous shocks. In particular, this study focuses on smartphone apps and examines differences between "digital" brands that primarily do business online and "phygital" brands that have already established their brands offline. We also distinguished the highly uncertain environment into multiple phases and found non-linear changes in the magnitude of the parameters. We find that phygital brands have different factors affecting their competitiveness compared to digital brands. The results also provide insights into the online channel strategies of retail companies that already have brand value offline.

1. Introduction

The outbreak of COVID-19 caused a significant economic and social impact (Centers for Disease Control and Prevention, 2022). In 2020 especially, many countries and regions restricted mobility, severely affecting passenger transportation and tourism markets (Rita et al., 2022). Not only did companies with physical stores lose sales opportunities, but international supply chains were also affected, resulting in significant financial losses (Ali et al., 2022). The International Monetary Fund (2021) reported a global GDP growth rate of −3.3%, and macro data also reveal a contraction in global economic activity. Nevertheless, some industries are expected to grow. Lockdowns and teleworking in large cities across the world restricted human contact, especially in 2020 (Nicola et al., 2020). Such restrictions led many businesses and schools to go online and digitalize their activities (Paunov and Planes-Satorra, 2021; Venkatesh, 2020; Neeley, 2020). In retailing, various previously provided in-person services are now moving online. Thus, "phygital" services, where physical services and experiences expand to digital, have become an important perspective in recent years (Banik, 2021; Banik and Gao, 2023; Mondal and Chakrabarti, 2021; Pangarkar et al., 2022).

Thus, the spread of COVID-19 has had a significant negative impact on existing face-to-face-based businesses. Brands with stores have been significantly affected by curfews, and therefore, a decrease in the frequency of store visits has also adversely affected services that complement the stores; this has reduced the usage of online apps for such brands (Li et al., 2022). For such businesses, the performance of the online channel is likely to have a significant impact on corporate performance. In that vein, there will likely be a difference in future competitiveness between brands that can and cannot respond to digitalization or phygitalization (Johnson and Barlow, 2021; Mondal, and Chakrabarti, 2021). Stocchi et al. (2021) examine online businesses in terms of brand power and corporate capabilities. To cope with large exogenous shocks, B2C companies, especially those with brick-and-mortar stores, need to expand their online channels and keep their customers connected. In particular, B2C brands with stores need to increase their digital sales and communication channels to develop resilience to exogenous shocks. In this uncertain situation, it is especially necessary to maintain brand competitiveness (Baumann and Piehler, 2020) and design a brand strategy focusing on the medium-to long-term perspective.

Against this background, this study focuses on the online marketing strategies of brands and how these strategies help to strengthen the competitiveness of these brands. The existing literature has examined both these aspects. Brand competitiveness can be seen as a derivative of brand equity and brand value (Aaker, 1991; Keller, 1993; Winzar et al., 2018). Similarly, the success or failure of online communication channels is also judged by whether they add value (Verhoef et al., 2021). Further, the literature has also focused on reactions to and resilience

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against temporary exogenous shocks, such as natural disasters and economic crises, as well as the supply chain resilience of organizations (Taleizadeh et al., 2020).

However, there are two research gaps in examining brand competitiveness resilience in online markets. First, multiple product categories with different origins and characteristics should be analyzed simultaneously to measure brand competitiveness, especially digital brand competitiveness. Previous studies have limited their analysis to a single product category. However, recent digital brand positioning studies have demonstrated that it is now possible to analyze multiple product categories simultaneously based on online user behavior (Culotta and Cutler, 2016; Yang et al., 2022). In online or mobile brand communication, brands in different product categories often communicate on the same social network service or other platforms. Therefore, brands are often evaluated across categories, and an analysis that includes multiple product categories is necessary to maintain a brand presence online (Stocchi et al., 2020; Mondal and Chakrabarti, 2021). In addition, the differences between the success factors of phygital brands (which predominately conducted face-to-face business before the pandemic but have expanded their brand contact points online) and digital brands (which predominately conducted business online before the pandemic) must be carefully monitored (Johnson and Barlow, 2021; Pangarkar et al., 2022).

The second research gap is the need for data from multiple time points. An exogenous shock, such as a pandemic, elicits a reaction over time, thus requiring observation over the long run. There are multiple stages of resilience to a crisis that should be examined over time (Paunov and Planes-Satorra, 2021). For example, Guthrie et al. (2021) tracked and analyzed consumption behavior between January and July 2020, and even during this period, significant trends were observed. The results of this study also demonstrated the importance of examining long-term changes in the changing environment of COVID-19. Several studies on brand competitiveness employ survey data from a single time point (Baumann et al., 2017; Winzar et al., 2018; Gupta et al., 2020). However, such data does not capture long-term changes. Therefore, it is necessary to examine the resilience of brand competitiveness over the long term, that is, over a year or more.

In this study, we analyze the mobile service market, a market that expanded significantly in 2020, to examine resilience to the COVID-19 crisis based on brand competitiveness. In particular, we compare short-term and long-term resilience and discuss the characteristics of resilient brands. We use long-term app usage data, including multiple categories, as well as online review data to analyze the relationship with past consumer attitudes.

2. Literature review

2.1. Brand competitiveness

Studies by Baumann et al. (2017), Winzar et al. (2018), and Gupta et al. (2020) have examined the added value that brands bring based on research. For example, many constructs have been proposed regarding the value that brands have, such as brand value research, brand equity (Aaker, 1991; Keller, 1993), and brand value chains (Keller and Lehmann, 2006). Such studies also mention elements of positioning; for example, Porter (1985) emphasized market competitiveness and defined constructs that symbolize substantial competitiveness within the market. Based on these previous studies, this study follows Winzar et al. (2018) to define the concept of brand competitiveness: *brand competitiveness is the market share estimation at a particular combination of price and brand features, relative to competitors' price/feature bundles.* Since this definition focuses on market share in particular, this study also discusses brand competitiveness focusing on market share.

Several approaches help to measure brand competitiveness. Winzar et al. (2018) used experiments to measure preferences. Baumann et al. (2017) used behavioral loyalty and used individual shares, following Keiningham et al. (2007), in addition to using future intentions as outcome variables. Brand equity can also be measured on a non-attribute basis (Park and Srinivasan, 1994), and on the idea that the residuals of the regression model are brand equity (Kamakura and Russell, 1993). Brand competitiveness can also be examined by analyzing market share as a measure of results. Krugman (1994) considered market share and its incremental value as a competitive strength. Similarly, Simon and Sullivan (1993) considered a high market share relative to book value as brand value. Some studies have defined and analyzed brand competitiveness based on data other than survey data, using experimental design methods.

2.2. COVID-19 and digitalization

Digitalization has dramatically improved the amount of data on consumer emotions and behavior, which is also used in marketing (Kannan and Li, 2017; Wedel and Kannan, 2016). In addition, exogenous shocks, such as the COVID-19 pandemic, can also help in understanding recent market trends in the mobile app industry. Sheth (2020) and Verma and Gustafsson (2020), among others, have studied the pandemic's effect on consumer and corporate behavior, and pointed to a significant change in such behavior after the spread of COVID-19 (Beaunoyer et al., 2020; Katsumata et al., 2022). Studies capturing changes from a consumer perspective have examined the impact of COVID-19 on consumer psychology from various aspects, including cyberchondria (Laato et al., 2020), socio-demographics and consumer behavior (Leung et al., 2020), and social class and ability to interpret information (Kim et al., 2020).

Information and communication technology (ICT), and hence digitalization, can also influence the lure of brick-and-mortar marketplaces. COVID-19 has pronounced the use of ICT in this regard. For example, in the case of public libraries, studies have shown that the presence of online apps is a major factor in the continued use of libraries (Chan et al., 2022). The increased use of food delivery apps is a comparable example in the case of restaurants (Dirsehan and Cankat, 2021; Kumar and Shah, 2021). These services have made great strides during the COVID-19 pandemic and are examples of digital transformation, as defined by Verhoef et al. (2021). Some studies have actually discussed its junction with digital transformation (Reuschel, Deist, and Maalaoui, 2022). However, we must consider that online-oriented brands and offline-oriented brands have different digitization strategies (Madsen and Petermans, 2020; Algharabat et al., 2020). Specifically, we also need to examine the key success factors of physical (offline) brands that have provided a physical customer experience and have entered digital platforms to become phygital brands (Johnson and Barlow, 2021; Banik, 2021; Banik and Gao, 2023; Mondal and Chakrabarti, 2021; Pangarkar et al., 2022). Thus, restrictions on in-person gatherings and communication, which were introduced because of COVID-19, have become an important turning point for digital transformation.

2.3. Hypotheses on factors affecting brand competitiveness

Based on the aforementioned studies, we derive hypotheses about the factors affecting brand competitiveness and the moderating effect of resilience stages in this and the following subsections.

Previous studies have examined the factors that directly and indirectly influence brand competitiveness (Baumann et al., 2017; Winzar et al., 2018; Gupta et al., 2020). Among these studies, Gupta et al. (2020) found that brand differentiation, marketing orientation, and strategic orientation significantly influence brand competitiveness. In addition, the relationship between brand value, brand equity, online reviews, and online channels has also been discussed in recent studies (Alzate et al., 2022). For example, some recent studies analyzed mobile apps from a brand value perspective (Stocchi et al., 2022; Qing and Haiying, 2021). The impact of brand competitiveness on exogenous shocks, which is the subject of analysis in this study, is discussed in terms of what brand equities were held before the exogenous shocks occurred (Aaker, 1991) and to what extent. Therefore, we derive hypotheses in terms of brand equity, especially the following three elements: brand loyalty, brand awareness, and perceived quality (Aaker, 1991; Algharabat et al., 2020).

H1 concerns brand loyalty. Brand loyalty is consumers' loyalty to a brand and is an antecedent of consumption behavior (Das, 2014; Lin and Wang, 2006). If brand loyalty is high before exogenous shocks, the shocks may also prevent customer disengagement and the resulting decline in brand competitiveness (Kim et al., 2021). This study also leads to hypotheses about the differences between phygital and digital brands. In particular, the impact of brand loyalty on brand competitiveness is expected to be greater for phygital brands, which have more customer contact points than digital brands (Banik, 2021; Banik and Gao, 2023). Based on these discussions, we assume the following hypotheses H1a and H1b.

H1a. The greater the brand loyalty before the exogenous shock, the higher the brand competitiveness after the shock.

H1b. Brand loyalty is more relevant for brand competitiveness for phygital brands than for digital brands.

H2 concerns brand awareness, one of the components of brand equity. Brand awareness is a precedent factor for positive consumer response (Das, 2014; Jara and Cliquet, 2012). From a market macro perspective, it is assumed that the more consumers are aware of the brand, the greater the positive impact on brand competitiveness. Also, when considering online brand awareness, the impact is assumed to be greater for digital brands whose business is primarily online than for phygital brands with physical channels (Stocchi et al., 2021).

H2a. The greater the brand awareness before the exogenous shock, the higher the brand competitiveness after the shock.

H2b. Brand awareness is more relevant for brand competitiveness for digital brands than for phygital brands.

H3 concerns the perceived quality of the brand, one of the components of brand equity (Aaker, 1991; Zeithaml, 1988). Perceived quality is consumers' evaluation of the quality of a product or brand. Therefore, it can be interpreted as the reputation of the brand. A higher perceived quality before an exogenous shock will be associated with higher brand competitiveness after the shock (Das, 2014; Jara and Cliquet, 2012). Regarding the differences in the magnitude of the impact of perceived online brand quality, Chan et al. (2022) demonstrates that the quality that users perceive for online channels or touchpoints is important even for businesses with offline channels. Therefore, perceived value is considered to be an important factor in phygital brands (Mondal and Chakrabarti, 2021). Based on the above discussion, unlike brand awareness, the impact of perceived quality on phygital brands is assumed to be higher than that of digital brands.

H3a. The greater the perceived quality of a brand before the exogenous shock, the higher the brand competitiveness after the shock.

H3b. Perceived quality of a brand is more relevant for brand competitiveness for phygital brands than for digital brands.

H4 concerns network positioning. Generally, network positioning may have an impact on firm performance (Gulati et al., 2000). Further, brand value and network positioning have been found to have an indirect influence on brand competitiveness (Dawar and Bagga, 2015). Studies in market structure analysis have discussed brand strength based on a brand's network position (e.g., Alzate et al., 2022; Netzer et al., 2012; Culotta and Cutler, 2016; Yang et al., 2022). In addition, considering the impact of positioning as discussed in the previous section (Porter, 1985; 1985), it is possible that brands that are more central in the digital market may have higher online brand competitiveness after an exogenous shock. The magnitude of the impact is also assumed to be greater for digital brands that are embedded in online markets.

H4a. The greater the centrality of a brand, the higher the brand competitiveness.

H4b. Centrality of a brand is more relevant for brand competitiveness for digital brands than for phygital brands.

H5 and H6 concern the impact of the strategic orientations of a brand (Voss and Voss, 2000; Gupta et al., 2020). Prior research has shown that strategic orientations influence brand competitiveness (Gupta et al., 2020). In this study, we consider two types of strategic orientation: market orientation and product orientation. Both higher market orientation and higher product orientation before an exogenous shock are assumed to positively affect brand competitiveness. However, the magnitude of the impact is expected to differ.

We derive a hypothesis about the degree of market orientation of brands. Customers are more likely to prefer market-oriented communication when they interact with phygital brands rather than digital ones, which lack physical contact points and multi-channel communication (Mondal and Chakrabarti, 2021; Pangarkar et al., 2022). Therefore, the magnitude of the impact of the higher market orientation of phygital brands on brand competitiveness is expected to be higher than that of digital brands.

In contrast, we anticipate a significantly lower correlation between brand product orientation and brand outcomes for phygital brands than for digital brands. For example, according to Mondal and Chakrabarti (2021), customers' attitudes toward phygital brands are not determined solely by digital channel quality. Also, in Banik and Gao (2023), the performance of phygital brands is examined from the aesthetics and entertainment aspects, and relatively speaking, the influence of product orientation is considered less significant than that of digital brands. Therefore, the quality of the product is considered to be more important to consumers for digital brands, where the digital channel is the main channel. The magnitude of this influence is expected to be higher than for phygital brands.

H5a. The greater the marketing orientation of a brand before the exogenous shock, the higher the brand competitiveness after the shock.

H5b. Marketing orientation of a brand is more relevant for brand competitiveness for phygital brands than for digital brands.

H6a. The greater the product orientation of a brand before the exogenous shock, the higher the brand competitiveness after the shock.

H6b. Product orientation of a brand is more relevant for brand competitiveness for digital brands than for phygital brands.

2.4. Hypothesis on exogenous shock and resilience

This study focuses on resilience as a key concept in the examination of brand competitiveness vis-à-vis COVID-19. Resilience is defined as the process of effectively negotiating, adapting, and managing significant sources of stress and trauma, or the human capacity to bounce back and adapt positively when faced with adversity or major stressors (Windle, 2011). Resilience helps to examine an individual's response to shocks. For example, studies have examined resilience in the context of online communication (Bermes, 2022), COVID-19, and consumer resilience (Bermes et al., 2020; Bermes, 2021). Numerous studies have considered the resilience concept to explain the process of recovery from not only individual shocks but also organizational and societal shocks (Lengnick-Hall et al., 2011; Sakurai and Chughtai, 2020; Taleizadeh et al., 2021). Pal et al. (2014) described organizational resilience as the ability to prepare in times of crisis and maintain superior organizational performance, which is conceptually similar to individual resilience.

In relation to corporate brand competitiveness, studies on resilience have used travel companies as a case study (Ngoc Su et al., 2021; Jiang et al., 2021). Studies have also examined shock-related resilience in online and offline channels (Li et al., 2022). Further, some studies have considered inter-organizational channels to consider supply chain resilience in terms of dynamic capability as the ability to respond to change (Ali et al., 2022; Taleizadeh et al., 2021; Liu et al., 2020; García-Arca et al., 2020; Iftikhar et al., 2021). These studies considered organizational capability as a factor in corporate resilience, based on the resource-based view (Wernerfelt, 1984; Barney, 1991), as well as dynamic capability (Teece, 2007; Teece et al., 1997). Exogenous shocks are temporary in natural disasters such as earthquakes and hurricanes (Sakurai and Chughtai, 2020), but the COVID-19 exogenous shock has persisted for a longer duration. As mentioned in the previous section, the study by Guthrie et al. (2021) also shows the importance of studying long-term changes in COVID-19 infection status. It is therefore useful to understand the nature of recovery from this shock. Therefore, this study discusses brand competitiveness by considering the three stages of resilience (also used by Paunov and Planes-Satorra, 2021). Based on the above considerations, this study assumes that different phases of resilience affect brand competitiveness to different degrees, leading to the following hypothesis.

H7. The factors affecting brand competitiveness in an uncertain environment differ across the resilience phases.

Fig. 1 shows a conceptual diagram of the three phases of resilience, "Absorption," "Adaption," and "Transformation," proposed by Paunov and Planes-Satorra (2021), Béné et al. (2012), and Hynes et al. (2020).

Fig. 2 shows a conceptual diagram of the analytical model corresponding to the hypotheses of this study. x_j is the brand-specific variable, w_t is the time-varying factor, and s_{jt} is brand competitiveness.

3. Data and model

3.1. Objective market: COVID-19 pandemic in Japan

First, we focus on the Japanese mobile app market. The analysis period is 32 months, from January 2019 to August 2021. To include the onset of COVID-19 in 2020 and to examine resilience since then, we examine the impact of factors with pre-infection status as an explanatory variable and monthly market share of post-infection periods as objective variables (Conz and Magnani, 2020).

We refer to data on the status of COVID-19 in Japan during the analysis period and surrounding data to provide an overview of the social and market conditions. As basic data, Fig. 3 shows (a) the number of infected persons and deaths, (b) the Google Trends search index, and (c) the Internet traffic. The first peak in the number of infected and fatalities is in 2020, followed by peaks in August 2020, and then January, May, and August 2021. In terms of government policy, the first state of emergency was declared from April 7 to May 25, 2020, the second from January 8 to March 21, 2021, the third from April 25 to June 20, 2021, and the fourth from July 12 to September 30, 2021. However, Google Trends indexes do not correspond to this data. The highest number of Google Trends searches occurred before April 2020, which is considered the first wave, and in the last week of February 2020, which was before the pandemic. This could be because, on February 27, the Prime Minister declared that all elementary, junior high, and high schools nationwide would be closed, significantly affecting routine life. For the Internet traffic in (c), data obtained on a monthly basis are shown from 2019. The dotted line is the predicted value of the change in the Internet traffic after 2020, estimated from the 2019 data ($y = 2.079 - 87719 + e, R^2 = 0.910$). We see an overall increasing trend, and while the fit is good up to February 2020, from March 2020 onward, traffic is well off the predicted value for 2019 and increasing more than the predicted value. In particular, there is a sharp increase from March to May 2020, which may be due to online classes in schools and teleworking.

3.2. Data

Next, we provide a detailed description of the apps to be analyzed. In this study, Android app usage behavior is the subject of analysis. According to the Mobile Society Research Institute (2021), Android's share of the mobile OS market was 52.6% in 2019, 54.2% in 2020, and 53.2% in 2021. In addition, in this study, individual apps are considered "brands" in order to analyze their competitiveness in the mobile market. Stocchi et al. (2021) also considered the product strategy of an app as a brand, and this study follows that approach in its analysis.

Two main types of data will be used. The first data is the app usage logs. The smartphone usage log data from the i-SSP (INTAGE single source panel) were collected by INTAGE, Inc. and are a database that records the usage behavior of all the apps on the smartphones of individual participating consumers. We obtained data on the date and time of use, the apps used, the users, and the duration of use. Although the monitors change every month, approximately 2000 users per month participate in the survey, which provided data that fairly accurately reflects overall market trends. The second type of data is app review data. The data for app reviews are obtained by scraping from Google Play (https://play.google.com/). For app reviews, we obtained data on the date and time the review was posted, the content of the review, the review score (from 1 to 5), and the vendor's reply to the review.

Apps for analysis are selected from this usage behavior data and review data. The procedure for selecting apps for analysis was as follows.

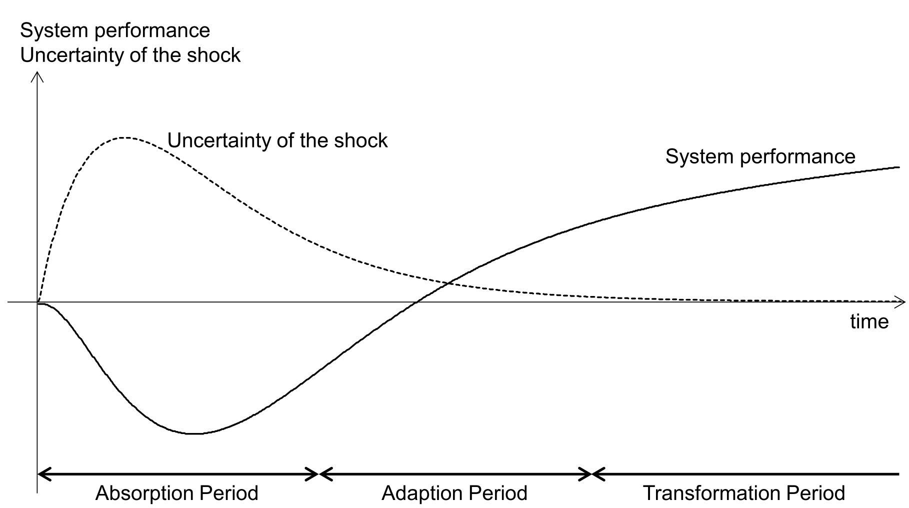

Fig. 1. Three successive phases of the resilience.

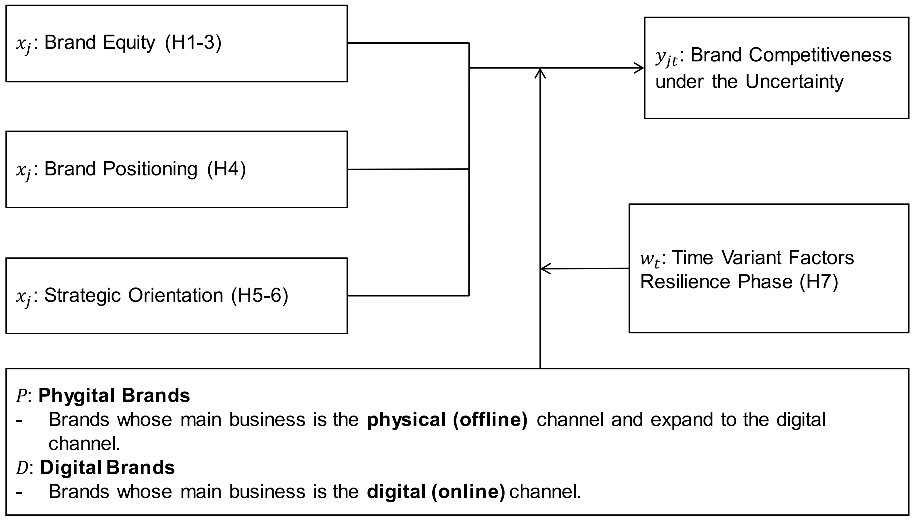

Fig. 2. Research model.

(1) The top 1048 apps with the highest usage frequency as of April 2020 were selected from the usage behavior data. The top 1048 apps account for more than 90% of all app launch logs by consumers, 97.1% in the month with the largest share, and 90.4% in the month with the smallest share.
(2) We used these apps to collect Google Play reviews. As some of the apps selected in (1) are pre-installed or system-related, depending on the model, only apps that consumers can freely download and use were included in the collection.
(3) Among these, 737 apps, for which more than 50 reviews were collected in 2019, were included in the analysis. This is the total number of brands analyzed in this study.
(4) Next, from the 737 apps, we separated brands that primarily offer in-person (physical) services, such as having a physical store, from brands that primarily offer online services. As a result, 50 phygital (mainly offline, expanding online) brands were selected. Specifically, we had 3 CVS, 6 supermarkets, 13 restaurants, 5 transportation brands, 5 drugstores, 4 banks, 1 logistics brand, and 13 other stores. Therefore, the number of digital (mainly online) brands is $737 - 50 = 687$. Although some of these digital brands, such as Amazon, have physical stores, they are classified as digital brands because they are brands that have grown primarily online (Mondal and Chakrabarti, 2021).

3.3. Variables

3.3.1. Brand competitiveness model

First, we defined indicators of brand competitiveness and resilience as objective variables. Brand competitiveness is defined as the share of the number of times an app is used. Market share is an important indicator and has been used to examine brand competitiveness. As discussed in the previous section, there are several measures of brand competitiveness. For example, Baumann et al. (2017) used the behavioral loyalty measure proposed by Keiningham et al. (2007), which measures the service share of individual customers. Among these studies, this study focuses on market share based on the definition by Winzar et al. (2018). To define market share, it is necessary to define the market space based on the product category or industry. While many previous studies on brand competitiveness have examined market shares limited to specific product or service categories, this study assumes a broader competitive relationship and includes all apps in its analysis since smartphone apps are the subject of this study. In recent studies of market structure analysis, it has been useful to include multiple product categories in the analysis, especially when discussing online inter-brand relationships (Yang et al., 2022). This study follows this framework and assumes a broad market for its analysis.

Several models with market share as the objective variable have been proposed in both the marketing and econometric fields (Nakanishi and Cooper, 1974; Cooper and Nakanishi, 1988; Berry, 1994; Berry et al., 1995). However, because the analysis here focuses on the number of times an app is used, we used Berry's (1994) model, which identifies parameters by assuming that brands other than those under analysis are external goods.

First, let s_{jt} be the share of usage frequency of brand j at time t ($t = 1, \cdots, T. j = 1, \cdots, J$). Next, let s_{0t} be the user share of smartphones, excluding the brands to be analyzed. As mentioned above, this market share for the outside goods s_{0t} is the share of the number of usages of all apps excluding the J apps that were included in the analysis. If there are J brands to be analyzed, then $\sum_{0=1}^{J} s_{jt} = 1$. Let v_{jt} be the source of brand competitiveness and let the relative market share be a function of the relative source of competitiveness v_{jt} as in the multinomial logit model, we obtain the relationship between s_{jt} and v_{jt} as follows:

$$s_{jt} = \frac{\exp(v_{jt})}{\sum_{l=0}^{J} \exp(v_{lt})} \tag{1}$$

Let $V_t = \sum_{l=0}^{J} \exp(v_{lt})$ and take the logarithm of both sides.

$$\log(s_{jt}) = v_{jt} - \log(V_t) \tag{2}$$

In particular, if $v_{0t} = 0$ as a relative value for external goods, we obtain the following value:

$$\log(s_{0t}) = -\log(V_t) \tag{3}$$

Here, taking the difference between $\log(s_{jt})$ and $\log(s_{0t})$, we obtain the relationship between the source of competitiveness v_{jt} and the observed market share.

$$\log(s_{jt}) - \log(s_{0t}) = v_{jt} - \log(V_t) - (-\log(V_t)) = v_{jt} \tag{4}$$

We assume the brand competitiveness of the analyzed brand $v_{jt} = \log(s_{jt}) - \log(s_{0t})$ is explained by the brand-specific variable x_j, the time-varying resilience phase variable w_t as a moderation variable, its interaction term, and the stochastic normal error ε_{jt} is included. We obtain the following equation.

$$v_{jt} = x_j\beta_x + w_t\beta_w + x_j w_t \beta_{xw} + \varepsilon_{jt} \tag{5}$$

Therefore, we can examine the factors explaining brand

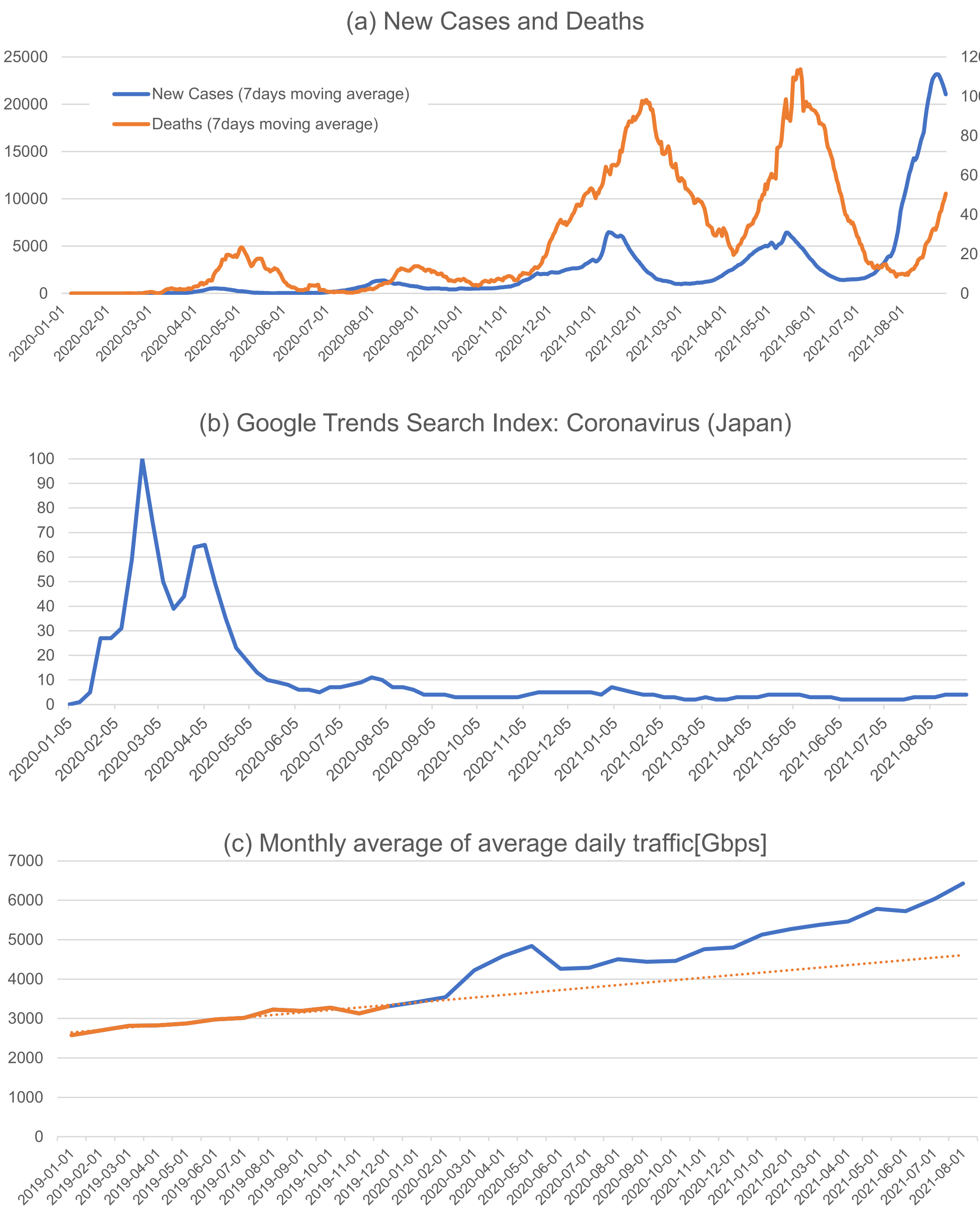

Fig. 3. Overall trends of the objective periods.
Source: (a) Ministry of Health, Labour, and Welfare in Japan (https://www.mhlw.go.jp/stf/covid-19/kokunainohasseijoukyou.html), (b) Google Trends (https://trends.google.com/trends/), (c) Ministry of Internal Affairs and Communications (https://www.soumu.go.jp/menu_news/s-news/01kiban04_02000202.html). Note that the dotted line (estimated traffic) is added by the authors.

competitiveness from a linear regression model with v_{jt} as the dependent variable. The model of competitiveness defined in this section has, as explanatory variables, a brand-specific factor x_j and a time-varying factor w_j. Each of these will be defined in the subsequent sections. Table 1 shows the detailed brand competitiveness operationalization.

3.3.2. *Explanatory variables*

First, we explain the definitions of the explanatory variables x_j as brand-specific factors. We classify brand-specific factors into three major constructs: brand equity (Aaker, 1991; Algharabat et al., 2020; Das, 2014), brand positioning (Netzer et al., 2012; Yang et al., 2022), and marketing/strategic orientation (Voss and Voss, 2000; Gupta et al., 2020).

Brand Equity: In this study, we incorporate three types of brand equity variables, brand loyalty, brand awareness, and perceived quality (Aaker, 1991; Algharabat et al., 2020; Das, 2014).

For the first variable, *Brand Loyalty*, we use the share of usage in the previous year. This variable is the number of customers before the

Table 1
Dependent variable.

Construct	Notation	Operationalization
Dependent Variable (Brand Competitiveness)	v_{jt}	From the following share of the objective brand (s_{jt}) and outside brands (s_{0t}), we obtain v_{jt} where $v_{jt} = \log(s_{jt}) - \log(s_{0t})$ and use this as the objective variable for brand competitiveness.
Share of Objective brands	s_{jt}	For objective app j ($j = 1, \cdots, J; J = 732$), use the share of the number of usages in month t of the analysis period.
Share of Outside Brands	s_{0t}	The share of the number of usages of all apps except for the $J = 732$ objective apps in analysis. For example, if the total number of app usages in month t is $1,000$ and the total number of usages of the J objective apps is 800 ($\sum_{j=1}^{J} p_{jt} = 800$), the number of usages of outside goods is 200, therefore, $s_{0t} = 0.2$. Since the model proposed by Berry (1994) requires the market share of external goods, we need to incorporate the term into the dependent variable.

exogenous shock and can be interpreted as the stock of the user base as it is the amount of previous loyalty (Guadagni and Little, 1983; Gedenk and Neslin, 1999). From the app usage logs, we obtained the monthly usage share for 2019, which is then weighted average to calculate the usage share for 2019 and used as the explanatory variable. The weighted average weight g_t is $g_t \propto (|t| + 1)^{-1}, \sum_{t=0}^{-11} g_t = 1$ with December 2019 as $t = 0$ and January 2019 as $t = -11$.

For the second variable, *Brand Awareness*, we use the number of online reviews. From the review data, we take the monthly average of the number of reviews in 2019 and use this value. For the number of reviews, "volume" is one of the main factors cited by others as an indicator to measure the competitiveness of an app (Dellarocas, 2003; Dellarocas et al., 2007). This study also examines the impact of this volume. The number of reviews is also calculated by month and weighted using the weights g_t above.

For the third variable, *Perceived Quality*, we use the review score, which is the outcome given by users to qualitative aspects of the app. As with the review data, this is also a weighted average of the 2019 review scores, aggregated by month. Review scores are emphasized as "valence" in the abovementioned studies (Chevalier and Mayzlin, 2006; Liu, 2006; Moe and Trusov, 2011; Moe and Schweidel, 2012) and are

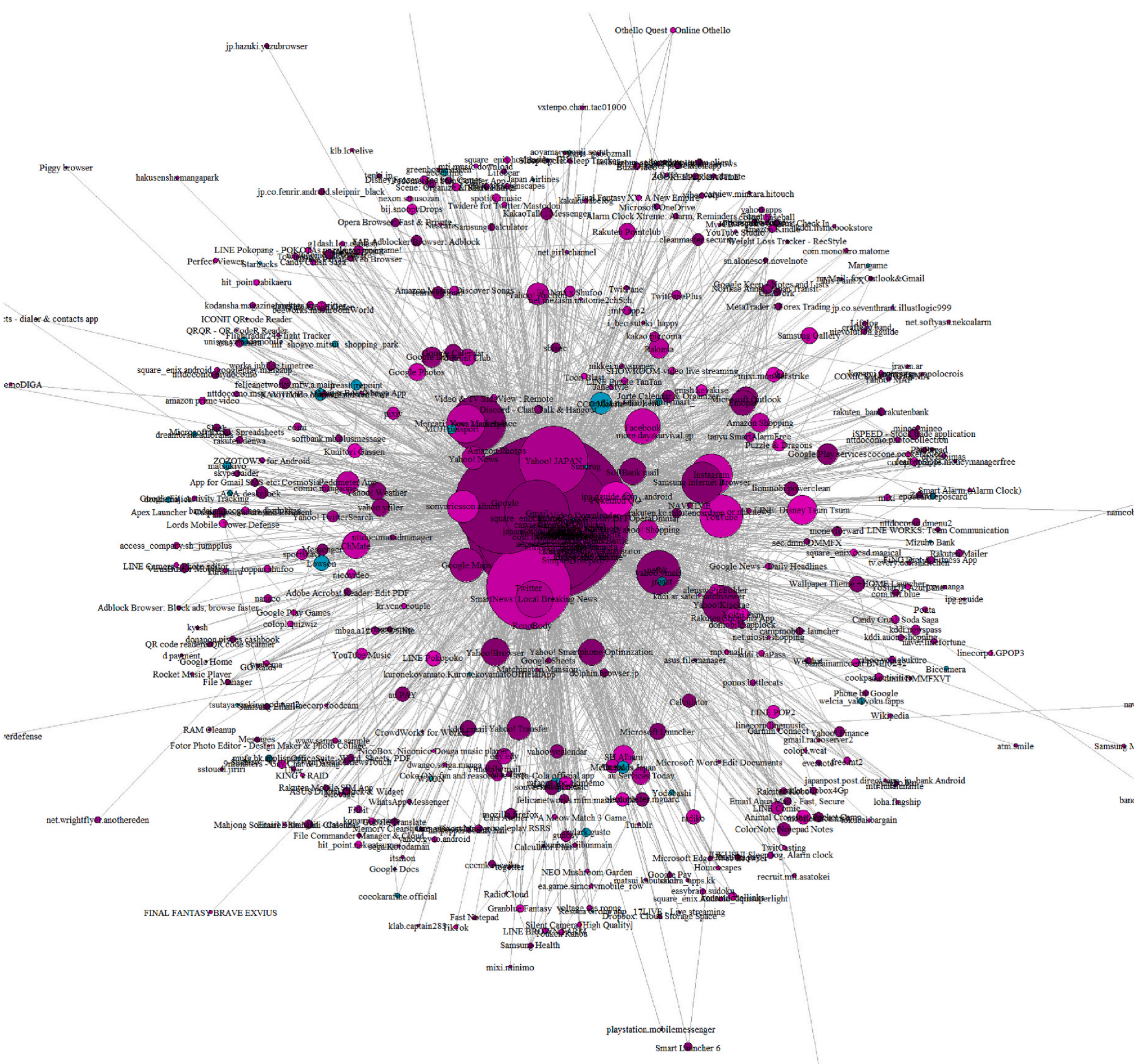

Fig. 4. Brand-brand network (January 2019)
Note: Purple: Digital brands, Light Blue: Phygital brands, Dark Color: Utilitarian brands, and Light Color: Hedonic brands. The center of the network is shown enlarged.

assumed to affect brand competitiveness. For review scores, as with the share of use and number of reviews, we take a weighted average.

Brand Positioning: Next, we define the indicators of brand positioning. Brand positioning uses network indicators (Freeman et al., 1979; Borgatti, 2005; Borgatti and Everett, 2006).

For the network indicator called *Centrality,* we used the brand-(user)-brand network because the app usage log data has the user id. Therefore, from the monthly usage logs, we created an undirected binary network that draws paths between apps used by the same users, from which we calculate the centrality index for network analysis. Yang et al. (2022) have also examined brand positioning from a brand-user network, and in this study, we also constructed a brand-brand network from the brand-user data to calculate centrality. For network centrality, we computed degree centrality, betweenness centrality, eigenvalue centrality, and page rank (Borgatti and Everett, 2006). However, because these four network centrality indices are highly correlated, we computed composite centrality, which is the average of the four centralities. Because users change every month, composite centrality is created for each month of 2019, and the weighted average of centrality is used as the explanatory variable. The weighted average weight g_t is the same as the number of reviews, review scores, and other variables. Fig. 4 shows the brand-brand network used as an explanatory variable for January 2019.

Strategic Orientation: Next, we measure the strategic orientation of a firm based on the amount of effort made by the firm. According to Gupta et al. (2020), brand competitiveness is influenced by a marketing orientation and a strategic orientation. Also, according to Voss and Voss (2000), there are three classifications: customer orientation, competitor orientation, and product/technology orientation. However, the relationship with competitors and other brands is discussed in the brand positioning section, and hence, market orientation and product orientation are the targets of our study.

First, for *Market Orientation,* we use the number of replies to reviews. For review responses, previous studies considered hotels (Proserpio and Zervas, 2017; Wang and Chaudhry, 2018; Chevalier et al., 2018), communication services (Ma et al., 2015), and e-commerce (Le and Ha, 2021). These empirical studies have shown a positive impact on marketing outcomes. In this study, we aggregate the total number of replies posted in 2019 for each app, add 1, and take the logarithm, and use that as a variable.

For *Product Orientation*, we also use the degree of version-upgrade of the app in 2019 as a variable. Product development investment in apps can be observed in the degree of version upgrades. In this study, we take the difference between the lowest and highest version observed in 2019, referring to the information on the app version attached to the review. In this study, major versions are weighted 1, minor versions are weighted 10^{-4}, and bug fixes are weighted 10^{-6}. For example, if the lowest version was 3.1.1 and the highest version was 5.2.1, the value would be 2.00201 because the major version went up 2 and the minor version also went up 2. If the major version is greater than 5, the value is 5.

Control Variable (Utilitarian Purpose): As a control variable, we incorporate the utilitarian score (Yin et al., 2017). The reason is that this study is analyzing apps from various usages and markets, and it is necessary to control for heterogeneity in app usage. The brand utilitarian score was also investigated for the app category by Yin et al. (2017) by applying research classifying products by utilitarian and hedonic goods (Kronrod and Danziger, 2013; Dhar and Wertenbroch, 2000). Because Yin et al. (2017) measured the utilitarian score for each category, we used this score. This classification is also valid when examining trends in online reviews (Rocklage and Fazio, 2020). We also use the values category for this study. However, there is some debate about the results and whether apps are used for utilitarian or hedonic motivation in situations of uncertainty (Kirk and Rifkin, 2020).

Table 2 shows the definitions of the brand-specific variables.

3.3.3. *Identification of resilience phases*

We first identified resilience phases from a model that assumes only resilience phases and monthly indices w_t as explanatory variables for v_{tj} in the model. First, we assumed three phases of resilience (Paunov and Planes-Satorra, 2021). Next, we assume an approximate duration for the resilience phases. Considering the COVID-19 indicators of infection spread and public concern in the previous section, we can assume that the absorption period began between February and April 2020, and the adaptation period began between June and December 2020, when the first emergency declaration ended. The transformation period is assumed to be after December 2020, and the detailed period will be determined by actual data. The number of possible combinations is 144, and estimation is performed using the market share model defined in the previous section, with the resilience period and month indexes as explanatory variables. Note that online and offline brands are estimated separately because they are considered to have different phases. We estimated models assuming 144 patterns of resilience phase transition

Table 2
Brand-specific variables (x_j).

Construct	Measurement	Operationalization	Related studies
Brand Equity			Aaker (1991), Algharabat et al. (2020), Das (2014)
Brand Loyalty	App Usage	A weighted average of usage shares from January to December 2019.	Guadagni and Little (1983), Gedenk and Neslin (1999)
Brand Awareness	Number of Reviews	Calculate the monthly total number of reviews posted in 2019 and use that weighted average.	Dellarocas (2003), Dellarocas et al. (2007)
Perceived Quality	Average Review Ratings	Calculate the average monthly score for reviews posted in 2019 and use that weighted average.	Chevalier and Mayzlin (2006), Liu (2006), Moe and Trusov (2011), Moe and Schweidel (2012)
Brand Positioning			Alzate et al. (2022), Netzer et al. (2012), Culotta and Cutler (2016); Yang et al. (2022)
Centrality	Brand-brand Network Centrality	Create a brand network for apps in each month of 2019 and calculate the average of degree centrality, betweenness centrality, eigenvalue centrality, and page rank for the network. Calculate the weighted average of monthly centrality in 2019.	Freeman et al. (1979), Borgatti (2005), Borgatti and Everett (2006)
Strategic Orientation			Gupta et al. (2020), Voss and Voss (2000)
Market Orientation	Review Reply	Use the number of review replies for reviews posted in 2019.	Proserpio and Zervas (2017), Wang and Chaudhry (2018), Chevalier et al. (2018), Ma et al. (2015), Le and Ha (2021)
Product Orientation	App Upgrade	Updates (version upgrades) of the application during 2019 were quantified and used as product orientation variables.	Gupta et al. (2020), Voss and Voss (2000)
Control Variable			
Utilitarian Purpose	Utilitarian score	Use the utilitarian score for the category to which each app belongs.	Yin et al. (2017), Rocklage and Fazio (2020)

timing for each of the online and offline brands and compared the models by AIC. The results reveal that the model with the best fit in terms of AIC goes through the phases as shown in Fig. 5 digital brands entered the absorption period in March 2020, the adaption period in July 2020, and then the transformation period in June 2021. On the other hand, phygital brands entered the absorption period later than online brands, in April 2020, but they enter the adaption period earlier than online brands, in June 2020. They also entered the transformation period in April 2021, which is also earlier than digital brands. Overall, the timing of the resilience phase changes for the digital and phygital brands are roughly synchronized, with a gap of two months at most, but they still differ from each other.

Table 3 summarizes the resilience phase indicators. Note that the timing of the phase changes for offline and online brands is slightly different. We also added the month index as a control variable to the model. This variable is used to absorb the effects of obsolescence and other effects of the passage of time between the explanatory variable and the objective variable.

4. Results

4.1. Results without assuming resilience phases

In this section, we first estimate a regression model that takes brand competitiveness in 2020–2021 after the exogenous shock as the objective variable and incorporates only x_j, the 2019 indicator, as the explanatory variable in order to examine the impact of brand competitiveness. The model does not assume a resilience phase. However, to absorb the effect of brand obsolescence, the month index is included as an explanatory variable. In this section, we also separate phygital brands and digital brands in the estimation. We can partially analyze the factors that contribute to brand competitiveness in the online market, and how the factors that contribute to brand competitiveness, differ between phygital and digital brands.

Table 4 shows the results of the analysis without assuming a resilience phase. The first thing we can see is that the factors that have a common influence on both phygital (P0) and digital (D0) brands are *Brand Loyalty*, *Customer Orientation*, *Market Orientation*, and *Product Orientation*. All of these factors have a positive impact on brand competitiveness. On the other hand, the factors affecting only digital brands are the *Brand Awareness*, and *Centrality*. Regarding the other

Table 3
Time variant factors (w_t).

Construct	Phygital brands	Digital brands
Absorption period	April 2020 to May 2020	March 2020 to June 2020
Adaption period	June 2020 to March 2021	July 2020 to May 2021
Transformation period	April 2021 to August 2021	June 2021 to August 2021
(Control variable) Month index	Month increment variable such that Jan 2020 = 1, Feb 2020 = 2, and so on.	Month increment variable such that Jan 2020 = 1, Feb 2020 = 2, and so on.

factor, *Perceived Quality*, the results supported the previous study only for phygital brands but were not significant for digital brands.

4.2. Results assuming phases of resilience

Next, Table 5 shows the results of the analysis assuming phases of resilience. First, we compare the tables in the previous section with the Adjusted R^2 from the table in this section to see if the explanatory power is improved by examining the heterogeneity of the effects of resilience phases. Adjusted R^2 is a suitable indicator for comparing models because its explanatory power decreases when the number of explanatory variables is excessively large. The phygital brands are 0.865 for the model that assumes no resilience phase (P0), 0.872 for the model that assumes a resilience phase but no interaction (P1), and 0.873 for the model that assumes an interaction (P2). The model with the interaction is the better model, albeit only slightly. In the digital brands, the model with no resilience phase (D0) was 0.675, the model with resilience but no interaction (D1) was 0.681, and the model with interaction (D2) was 0.685, indicating that the model with resilience phase was better than the model without interaction. The model assumes the interaction is the best fit.

Fig. 6 illustrates the effects of interactions obtained from models (P2) and (D2). For the interaction effects, the marginal effect of variable k on the objective variable v in resilience phase l is $\partial v / \partial w_l = \beta_k + \beta_{kl}$, and the solid line in Fig. 6 is this value. The standard error is $SE(\beta_k + \beta_{kl}) = \sqrt{Var(k) + Var(kl) + 2Cov(k, kl)}$, from which the 95% confidence interval is calculated and shown by the dotted line. Overall, the figure shows that the magnitude of the impact varies non-linearly during the COVID-19 pandemic, indicating that the factors affecting brand competitiveness and their strength are changing in an unpredictable

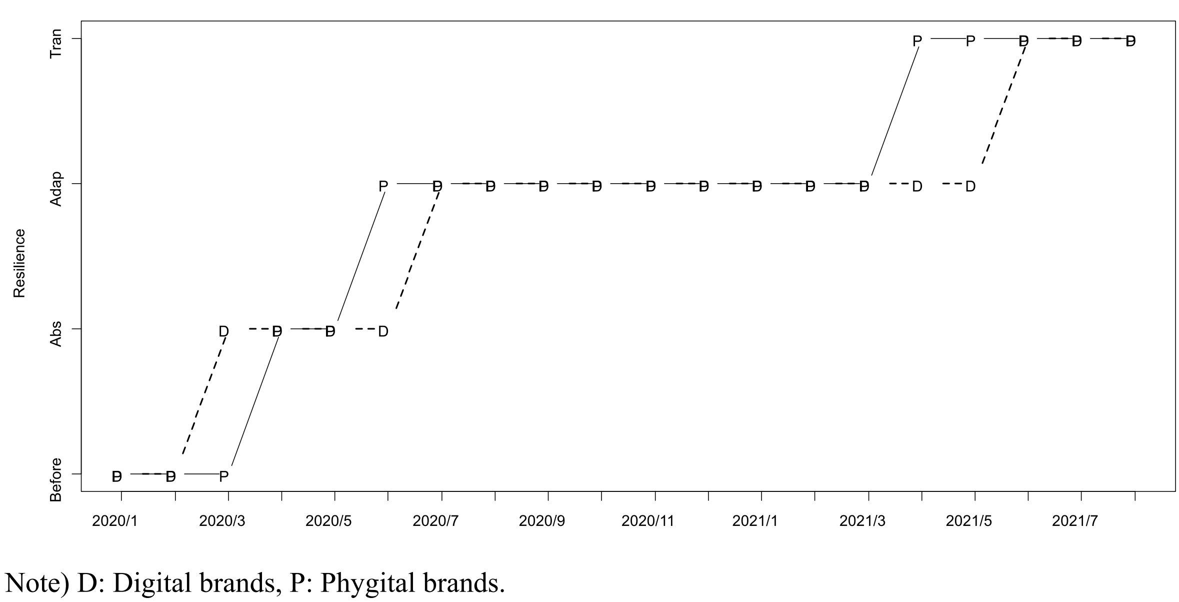

Fig. 5. Phases of resilience
Note) D: Digital brands, P: Phygital brands.

Table 4
Results of the analysis without assuming phases of resilience.

Dependent variable:	Brand Competitiveness		
Model	(A0)	(P0)	(D0)
	Overall	Phygital brands	Digital brands
Brand Equity			
H1a: Brand Loyalty (App Usage)	0.680***	0.892***	0.674***
	(0.008)	(0.024)	(0.009)
H2a: Brand Awareness (Number of Reviews)	0.086***	0.026	0.088***
	(0.009)	(0.019)	(0.009)
H3a Perceived Quality (Review Rating)	−0.023	0.095***	−0.029†
	(0.014)	(0.024)	(0.015)
Brand Positioning			
H4a: Centrality (Network Centrality)	0.306***	0.035	0.311***
	(0.019)	(0.068)	(0.021)
Strategic Orientation			
H5a: Market Orientation (Review Reply)	0.010**	0.088***	0.009*
	(0.004)	(0.012)	(0.004)
H6a: Product Orientation (App Upgrade)	0.067***	0.073*	0.067***
	(0.009)	(0.032)	(0.009)
Control Variable/Intercept			
Utilitarian Purpose	0.306***	0.035	0.311***
	(0.019)	(0.068)	(0.021)
Month_Index	−0.075***	−0.054***	−0.077***
	(0.001)	(0.002)	(0.002)
Constant	0.443***	2.127***	0.425***
	(0.093)	(0.256)	(0.098)
Observations	12,613	916	11,697
R2	0.681	0.867	0.675
Adjusted R2	0.681	0.865	0.675
F Statistic	3360.414***	736.344***	3037.348***

Note) †:p < 0.1, *:p < 0.05, **:p < 0.01, ***:p < 0.001.

environment. Fig. 6 shows that more detailed changes are obtained than in the model without assuming the resilience phase in the previous section. First, the impact of *Brand Loyalty* (app usage) is large and has a positive impact throughout the period, but the magnitude of the impact is decreasing online. The impact of *Brand Awareness* (number of reviews) is stronger for digital brands after the impact of COVID-19 increases, suggesting that the size of the number of reviews tends to have an impact in an environment of high uncertainty. On the other hand, for phygital brands, the effect of the number of reviews is positive but not significant. Next, for *Perceived Quality* (review rating), phygital brands show a larger impact in the adaption and transformation periods, while digital brands not only show no positive impact, but also a negative impact in the absorption period. The absorption period is the most uncertain period, and consumer behavior during this period also seems to have unpredictable aspects. *Centrality* (network centrality) has a strong positive impact only for digital brands, which may be because phygital brands are not necessarily embedded in online usage networks (Uzzi, 1996; Burt, 2004), and thus, the impact could not be measured. Conversely, phygital brands are less likely than digital brands to be influenced by their network position in terms of outcomes. As for the *Market Orientation* (review reply), phygital brands have a large positive impact, but this is thought to be because users of phygital brands are accustomed to face-to-face consumption behavior and therefore seek to communicate with the company in the app as well. On the other hand, digital brands showed more market share gains for brands with greater *Product Orientation* (upgrade). This could also be because digital brands primarily serve the app user experience, and therefore, their investment in apps is likely to influence this result. Phygital brands also have stores, and investment in those stores is also necessary to maintain customer loyalty, so investment in apps does not necessarily lead to an increase in users.

5. Discussion

5.1. Discussion of hypotheses and results

In this section, we test the hypotheses based on the results of the analysis. First, the results presented in Tables 4 and 5 allow us to examine hypotheses H1a through H6a. Since the analysis is conducted separately for phygital and digital brands, models H1a through H6a are examined separately. The coefficients for the hypotheses are approximately the same for both models. The results are the same for Model (D0) in Table 4 and Model (D1) in Table 5, both of which are for digital brands.

However, since hypotheses H1b through H6b require examining the difference in the strength of the influence of the phygital and digital brands, a test of the difference in coefficients is conducted by comparing two coefficients (P0)-(D0), and (P1)-(D1). Since it is not straightforward to compare (P2)-(D2), we compare the above models to evaluate the hypotheses. In addition, Table 5 and Fig. 6 which summarized the result of Model (P2) and (D2) show that although there are differences among phases, the overall trends are roughly the same as (P1)-(D1) and (P0)-(D0).

Table 6 shows the results of coefficient comparisons. A positive value indicates a larger coefficient for the phygital brand, while a negative value indicates a larger coefficient for the digital brand. This demonstrates that the comparison results for both models show the same trend. Significant differences are obtained for *Brand Loyalty*, *Perceived Quality*, and *Market Orientation*. On the other hand, differences of the *Centrality* coefficients were $0.1 > p \geq 0.05$, indicating that the differences were marginally significant. No significant differences were found for the other coefficients.

Table 7 summarizes the results of the examination of the hypotheses. For H1a through H6a, we refer to the signs of the coefficients obtained from Tables 4 and 5 as the basis for the evaluation. H1b through H6b are based on the comparison of the coefficients obtained from Table 6. For H7, the difference in the goodness of fit of the model that assumes the multiple phases of resilience and the model that does not assume the result of assuming the phases of resilience is used as the basis for evaluation.

Regarding the results of hypotheses H1 through H6, H1a, which examined brand loyalty, was supported for both digital and physical brands, and H1b, which assumed that the impact of phygital brands is larger, was also supported. Next, H2a, which examined brand awareness, was supported for digital brands but not for phygital brands. H2b, which examined the difference between the two coefficients, was also not supported. H3a, which examined perceived quality, was supported by a positive and significant result only for the phygital brand, while H3b, which examined the difference between the phygital brand and the digital brand, was supported. For Centrality, H4a was supported only for digital brands because their impact was positive and significant, but H4b was not supported because the differences in coefficients were not significant (the results were marginally significant). H5a and H6a were supported by positive and significant results for both digital and phygital brands. However, for H5b and H6b, which examined the difference between the two, only H5b was supported.

For H7, we examined the overall goodness of fit comparing models without and with the resilience phase assumption, as described in the previous section. In particular, the Adjusted R^2 value is used in this study. This is an appropriate measure of model comparison because it penalizes models with many explanatory variables. The results show that for phygital brands, the Adjusted R^2 for Model (P0), which assumes no resilience phase, is 0.865; Model (P1), which assumes a resilience phase but no interaction, is 0.872; and Model (P2), which also assumes interaction, is 0.873, indicating that the model that takes resilience phases into account has an improved fit. Similarly, for digital brands, the Adjusted R^2 for Model (D0) is 0.675, Model (D1) is 0.681, and Model (D2) is 0.685. Thus, we can state that H7 is supported.

Table 5
Analysis results assuming resilience phases.

Dependent Variable	Phygital					Digital				
Model	(P1)	(P2)				(D1)	(D2)			
	No Interaction	With Interaction				No Interaction	With Interaction			
		Direct Effect		Interaction			Direct Effect		Interaction	
			Absorption	Adaption	Transformation			Absorption	Adaption	Transformation
Brand Equity										
H1a: Brand Loyalty (App Usage)	0.891*** (0.024)	1.005*** (0.061)	−0.160† (0.096)	−0.143* (0.069)	−0.106 (0.078)	0.675*** (0.009)	0.853*** (0.027)	−0.179*** (0.033)	−0.197*** (0.029)	−0.229*** (0.035)
H2a: Awareness (Number of Reviews)	0.027 (0.018)	−0.054 (0.047)	0.055 (0.074)	0.096† (0.053)	0.107† (0.059)	0.088*** (0.009)	0.026 (0.029)	0.062† (0.035)	0.068* (0.031)	0.080* (0.037)
H3a: Perceived Quality (Review Rating)	0.094*** (0.024)	0.029 (0.060)	−0.018 (0.095)	0.082 (0.068)	0.107 (0.077)	−0.029† (0.015)	−0.010 (0.046)	−0.064 (0.057)	−0.008 (0.051)	−0.002 (0.061)
Brand Positioning										
H4a: Centrality (Network Centrality)	0.037 (0.066)	−0.023 (0.169)	0.312 (0.267)	0.083 (0.193)	−0.057 (0.215)	0.312*** (0.021)	0.084 (0.064)	0.033 (0.079)	0.304*** (0.070)	0.369*** (0.084)
Strategic Orientation										
H5a: Market Orientation (Review Reply)	0.088*** (0.012)	0.062* (0.030)	−0.007 (0.047)	0.031 (0.034)	0.044 (0.037)	0.009* (0.004)	0.012 (0.012)	0.009 (0.015)	−0.004 (0.013)	−0.016 (0.016)
H6a: Product Orientation (Upgrade)	0.074* (0.031)	0.023 (0.079)	−0.105 (0.126)	0.090 (0.091)	0.063 (0.101)	0.067*** (0.009)	0.027 (0.028)	0.020 (0.034)	0.050† (0.030)	0.057 (0.036)
Control Variable										
Utilitarian Purpose	0.001 (0.005)	0.002 (0.013)	0.002 (0.021)	0.001 (0.015)	−0.006 (0.017)	0.017*** (0.002)	0.010 (0.007)	0.002 (0.008)	0.008 (0.007)	0.015† (0.009)
Time variant factors										
Absorption	0.260*** (0.056)	−1.500 (1.008)				0.544*** (0.036)	−1.130** (0.365)			
Adaption	0.265*** (0.064)	−1.670* (0.728)				0.435*** (0.049)	−1.643*** (0.327)			
Transformation	0.160 (0.106)	−1.451† (0.818)				0.544*** (0.073)	−1.869*** (0.394)			
Month index	−0.058*** (0.006)	−0.058*** (0.006)				−0.089*** (0.004)	−0.089*** (0.004)			
Intercept	1.965*** (0.251)	3.517*** (0.637)				0.123 (0.099)	1.957*** (0.298)			
Observations	916	916				11,697	11,697			
R2	0.873	0.877				0.682	0.686			
Adjusted R2	0.872	0.873				0.681	0.685			
F statistic	566.219***	196.920***				2275.053***	794.856***			

Note) †:p < 0.1, *:p < 0.05, **:p < 0.01, ***:p < 0.001.

5.2. *Theoretical contributions*

This study makes two major contributions to the existing literature on brand competitiveness. First, it examines a method for measuring brand competitiveness using observational data rather than survey data. Because studies on brand competitiveness have typically used survey data (Baumann et al., 2017; Winzar et al., 2018; Gupta et al., 2020), it has been difficult to examine cross-brand trends with a large number of brands in the analysis, but this study was able to propose one solution to this problem. Second, this study examines the dynamic process of resilience. Survey data are effective when they are a snapshot at a single point in time and subject to analysis, but when they are examined across multiple time points, they are much more costly. Moreover, it is difficult to measure past psychological states, making comparisons with "prior" states difficult, especially in studies that target changes over time. By using online review data, this study was able to examine changes in factors affecting brand competitiveness over time. Future issues regarding the channel going online were also raised by Kannan and Li (2017); this study also proposes a solution to this problem. In particular, one of the contributions of this study is to identify key success factors in retailers' phygital retailing strategies (Sanita and Banik, 2023; Mondal and Chakrabarti, 2021) by behavioral datasets, which have been a focus in recent years.

This study also has contributed to the literature on resilience during the COVID-19 pandemic. This study used Paunov and Planes-Satorra's (2021) framework, with an online perspective to examine the impact of discontinuous exogenous shocks; the framework of this study can be used for a variety of changes. In the past, the world economy experienced major localized epidemics such as MARS and SARS (Cheng et al., 2022), and exogenous shocks from natural disasters (Sakurai and Chughtai, 2020) are also expected to occur in the future. From that perspective, the framework in this study can be used to examine consumer behavior in such an uncertain environment.

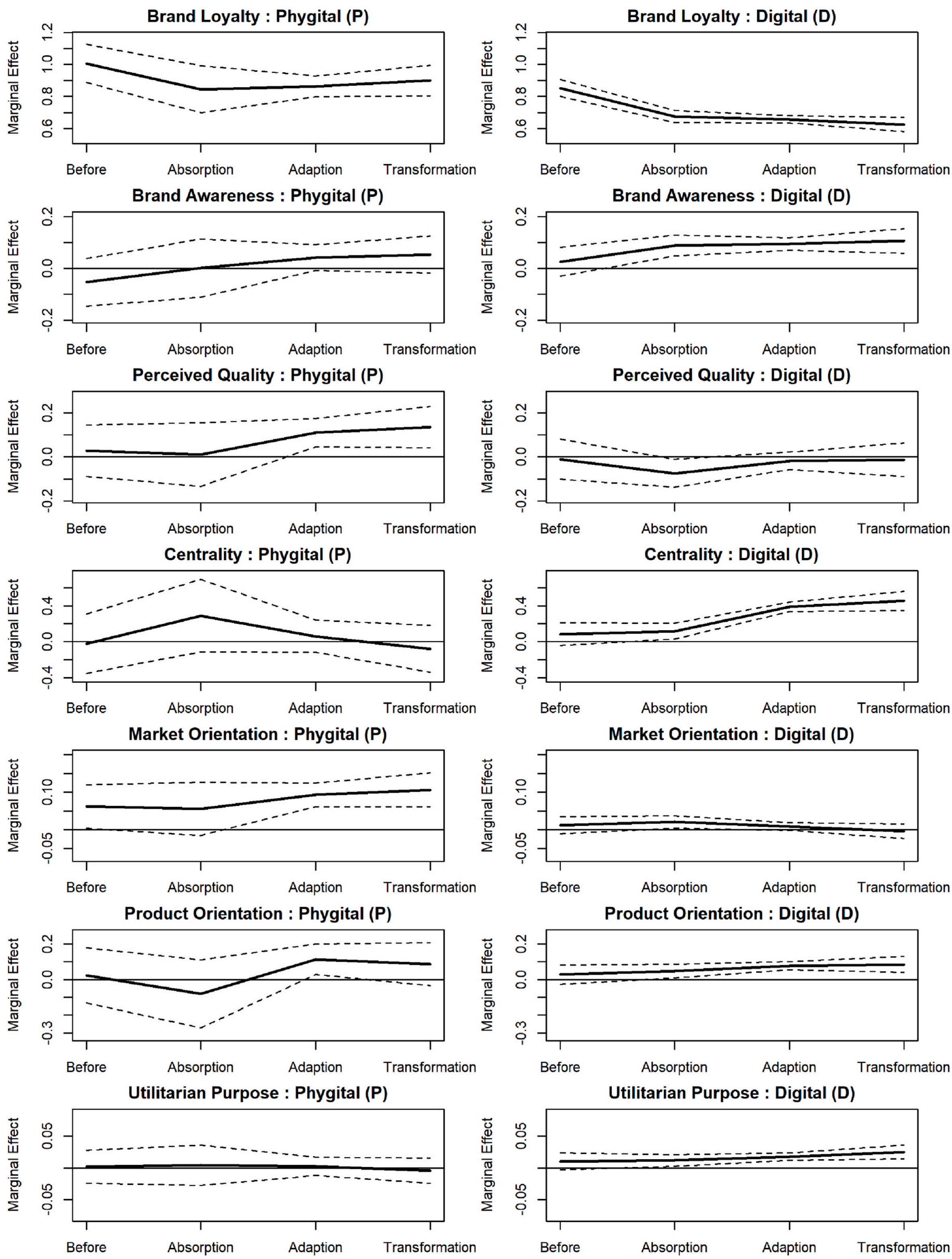

Fig. 6. Marginal effect of explanatory variables
Note: Solid line: Mean, Dotted line: Critical value of 95% confidence interval.

5.3. Practical contribution

The results of this study have implications for brands that have some degree of offline operations, including retailers with physical stores. While companies with physical stores needed to develop their online channels in 2020 due to the spread of COVID-19, the results of this study show that requirements for success in the online channel are different between phygital and digital brands. The analysis results reveal the following differences in the desirable online strategies of the phygital and digital brands. In the following, we summarize the individual factors and managerial implications:

Table 6
Result of the test for the difference of coefficients.

	Model (P0) and (D0)	Model (P1) and (D1)
Brand Equity		
H1b: Brand Loyalty *(App Usage)*	0.217*** (0.056)	0.216*** (0.056)
H2b: Brand Awareness *(Number of Reviews)*	−0.062 (0.044)	−0.061 (0.043)
H3b: Perceived Quality *(Average Review Ratings)*	0.124* (0.057)	0.123* (0.056)
Brand Positioning		
H4b: Centrality *(Network Centrality)*	−0.277† (0.156)	−0.275† (0.154)
Strategic Orientation		
H5b: Market Orientation *(Review Reply)*	0.079** (0.027)	0.079** (0.027)
H6b: Product Orientation *(App Upgrade)*	0.006 (0.073)	0.007 (0.072)

Note: †:$p < 0.1$, *:$p < 0.05$, **:$p < 0.01$, ***:$p < 0.001$.

(1) The impact of *Brand Awareness* measured by the number of reviews was significantly positive for digital brands, but not for phygital brands. Generally, brand competitiveness is positively related to the number of reviews, and the results for digital brands are consistent with previous findings because the brand contact points for digital brands are limited to online. However, phygital brands also have offline brand contact points, and it is likely that the number of online reviews is not enough to evaluate the attractiveness of the brand. However, although the parameters were significant for digital brands and non-significant for phygital brands, no significant results were obtained for the differences between these parameters.
(2) The impact of *Centrality*, in other words, network positioning, also shows a similar result to the number of reviews. For digital brands, the online network positioning positively affects brand competitiveness, while there is no significant relationship for phygital brands. The phygital brands are not fully embedded in the digital marketplace, so the result implies that positioning on mobile platforms is not the only factor in improving brand competitiveness.
(3) A factor affecting brand competitiveness for phygital brands is *Market Orientation*, measured by the frequency of replies to reviews. For digital brands, the frequency of replies to reviews from the brand side has no positive impact on the adaption and transformation phases. This implies that phygital brand customers are more likely than digital brand customers to seek a face-to-face customer experience. Therefore, they also desire communication even in the online touchpoint. This suggests that phygital brand customers need a different customer experience than digital brand customers.
(4) In addition, since online channels such as apps are the core value for both phygital and digital brands, *Product Orientation*, measured by the frequency of upgrades has a significant positive impact. This indicates that investment in online channels is necessary to keep their brand competitiveness.

These findings can also provide insights for brand managers of physical retail brands looking to expand into the digital channel (Sanita and Banik, 2023). According to the Ministry of Economy, Trade, and Industry (2022), the online retail market has been growing since the COVID-19 pandemic, and the importance of online channels, especially mobile channels, is expected to increase in the future. In the online channel, it is necessary to consider brands outside the industry to which the company belongs across product categories (Yang et al., 2022). This study was able to examine the factors of brand competitiveness in the online channel by analyzing multiple product categories.

6. Limitations and future directions

We would like to highlight two limitations of this study, along with directions for future research. First, although this study used smartphone usage logs and online review data to examine the brand competitiveness, it is difficult to conclude that the usage share and other indicators from online reviews are conceptually perfectly consistent as variables for brand competitiveness and its factors. This study used such data because of the need for data over time, but the validity of the variables should be further examined; future research should also conduct a content analysis of textual data from reviews (Alzate et al., 2022). Analytical frameworks have been developed in the marketing field in recent years, and the use of these data should be considered in the future (Berger et al., 2020; Humphreys and Wang, 2018; Balducci and Marinova, 2018).

Second, although this study dealt with data from 2019 to 2021 in

Table 7
Result of the hypotheses testing.

Construct			Coefficient Upper: Phygital(P) Lower: Digital(D)			Difference
Brand Equity						
Brand Loyalty	H1a	$\beta^P > 0$	Supported	H1b	$\beta^P > \beta^D$	Supported
		$\beta^D > 0$	Supported			
Brand Awareness	H2a	$\beta^P > 0$	Not supported	H2b	$\beta^P < \beta^D$	Not supported
		$\beta^D > 0$	Supported			
Perceived Quality	H3a	$\beta^P > 0$	Supported	H3b	$\beta^P > \beta^D$	Supported
		$\beta^D > 0$	Not supported			
Brand Positioning						
Centrality	H4a	$\beta^P > 0$	Not supported	H4b	$\beta^P < \beta^D$	Not supported
		$\beta^D > 0$	Supported			
Strategic Orientation						
Market Orientation	H5a	$\beta^P > 0$	Supported	H5b	$\beta^P > \beta^D$	Supported
		$\beta^D > 0$	Supported			
Product Orientation	H6a	$\beta^P > 0$	Supported	H6b	$\beta^P < \beta^D$	Not supported
		$\beta^D > 0$	Supported			
Resilience			Model Comparison			
Resilience Stage	H7		Supported			

Japan, it is necessary to test the structure with similar data in other countries and regions to verify the robustness of the results obtained in this study. Moreover, COVID-19 infections have periodically expanded and converged even after the analysis period considered in this study. Although the virus is becoming less powerful, it still has a significant socioeconomic impact. Future studies should verify this over a longer analysis period.

Declaration of competing interest

The authors have no conflicts of interest directly relevant to the content of this article.

Data availability

The data that has been used is confidential.

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