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Network effects, word of mouth, and entry performance: A study of digital freemium products

Noman SHAHEER

Liang CHEN
Singapore Management University, liangchen@smu.edu.sg

Jingtao YI

Sali LI

Huiwen SU

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Noman Shaheer [a], Liang Chen [b], Jingtao Yi [c,*], Sali Li [d], Huiwen Su [e]
a Discipline of International Business, The University of Sydney Business School, The University of Sydney, Sydney, NSW, Australia
b Department of Strategy and Entrepreneurship, Lee Kong Chian School of Business, Singapore Management University, Singapore
c Renmin Business School, Renmin University of China, Beijing, China
d International Business Department, Darla Moore School of Business, University of South Carolina, Columbia, South Carolina, United States
e School of Economics and Management, Fuzhou University, Fujian, China
Contact: yijingtao@rmbs.ruc.edu.cn (J. Yi) * Corresponding author

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Abstract: International entry research rarely examines strategies affecting entry performance in a target country, largely due to data limitations in the traditional multinational enterprise setting. However, the emergence of digital business with trackable international performance data helps address this gap. We utilize digital freemium products as our research context to examine the effect of two major demand-side strategies associated with freemium products, network effects and word-of-mouth (WOM), on entry performance across different institutional environments. By analyzing 1,891 freemium games, we show that lower network readiness of a target country strengthens the impact of network effects on entry performance whereas higher network readiness strengthens the impact of WOM. Our findings generate new insights by integrating the literature on foreign entry performance and digital internationalization.

Keywords: Digital freemium product, Demand-side perspective, Network readiness, International market entry, Mobile apps

1. Introduction

International market entry has been a major theme in the field of international business (IB). Extant research forms a comprehensive body of knowledge on entry mode and location choices (e.g., Boddewyn & Peng, 2021; Boeh & Beamish, 2012; Buckley & Casson, 1998; Hill et al., 1990), yet two notable shortcomings remain. First, the literature is dominated by an efficiency perspective, where entry is considered mostly a decision by which firms maximize efficiency gains and minimize transaction costs (e.g., Anderson & Gatignon, 1986; Brouthers, 2002; Jell-Ojobor et al., 2022). Second, much less is known about entry performance in a given target country, arguably the ultimate big question for IB scholars (Peng, 2004). To address these gaps, our study utilizes the internationalization of digital businesses as a novel context to examine entry performance. Since digital products can gain direct access to global users from their inception (Brouthers et al., 2022; Shaheer et al., 2020), foreign entry becomes much less a decision based on transaction cost minimization, allowing us to go beyond the efficiency perspective. In addition, the performance of these digital products can be accurately tracked and assessed, allowing us to investigate the strategic factors affecting their entry performance in different institutional environments.

In this paper, we take a demand-side perspective to evaluate key strategic factors for entry performance of digital freemium products that do not require any upfront payments and earn by charging users for add-on features (Boudreau et al., 2022; Rietveld & Ploog, 2022). Demand-side perspective prioritizes consumer needs, suggesting that firms improve their performance largely by aligning their strategies with customer preferences (Priem et al., 2013, 2007). Extending the demand-side perspective, we suggest that distinct strategic factors are likely to improve entry performance of digital freemium products in different countries because user preferences vary substantially acorss institutional environments (e.g., Shaheer et al., 2020; Siqueira et al., 2015).

Prior research particularly identifies two key strategic factors critical for performance of digital freemium products. First, scholars (Boudreau et al., 2022; Cheng & Liu, 2012; Miric & Jeppesen, 2020; Rietveld & Ploog, 2022) highlight the role of network effects, noting that freemium products with social features can facilitate rapid diffusion based on network externalities. Social functionalities can enable user interactions and help build an early lead in network size, creating self-reinforcing demand-side economies of scale and stimulating freemium products'

diffusion and performance. Second, marketing scholars (Arora et al., 2017; Liu et al., 2014) identify word-of-mouth (WOM) as another key strategic factor to enhance performance. Freemium products generate WOM by addressing similar preferences of specific user segments, which leads to greater user satisfaction and thus superior performance (Claussen et al., 2013; Onofrei et al., 2022; Tidhar & Eisenhardt, 2020). The research implies, however, that generating network effects from social features and delivering WOM via high user satisfaction may not always be compatible as both strategic factors align with different customer preferences. Instead, we argue that both strategic factors may represent distinct pathways that may lead to superior performance in different countries based on their fit with customer preferences in a country.

Extending the demand-side perspective, we seek to distinguish the impact of incorporating social features and generating WOM on the entry performance of digital freemium products across different demand environments. While previous studies attribute the growing importance of network effects and WOM to the widespread availability of digital infrastructure (Dou et al., 2013; Monaghan et al., 2020; Parker & Van Alstyne, 2005), relatively little work has looked at substantial variations across countries in digital infrastructure. To fill this gap, we focus on the institutional dimension of network readiness, defined as the extent to which a country leverages digital technologies in economic and social lives (Baller et al., 2016). Following the demand-side perspective (Priem et al., 2013; Priem et al., 2018), we argue that the network readiness of target countries will strengthen the effect of WOM but reduce the impact of network effects on entry performance of freemium products. We find supporting evidence after tracking the performance of 1891 gaming apps across 57 countries over a period of 24 months.

Our study complements existing research on international market entry, which mainly focuses on entry mode and location choices, by examining entry performance for digital freemium products that become instantly accessible to users worldwide. With low costs of technology development and zero marginal cost of servicing new users, the traditional strategic trade-off between low cost and product differentiation (e.g., Kim et al., 2004; Porter, 1980; Roth & Morrison, 1992) may not be relevant for digital freemium products that can simultaneously pursue both positions by developing novel digital technologies and offering them for free via the freemium model (Boudreau, 2012; Casadesus-Masanell & Zhu, 2013; Rietveld, 2018). Such unique dynamics indicate the need to explore new strategic trade-offs on which firms could build distinct positional advantages to improve their performance. We address this gap by identifying novel positional advantages for digital internationalization, which are analogous to Porter's (1980) seminal conceptualization of cost leadership and differentiation but differ notably from received wisdom owing to the unique demand-side advantages available to digital freemium products. We further explore the institutional boundaries of both advantages and shed light on the strategic fit of these strategies with demand conditions in target countries by highlighting a unique yet understudied dimension of institutional environments which is critical for digital internationalization. These findings enrich the current understanding of how digital products improve market entry performance and international marketing in the digital economy (Jean & Kim, 2020; Jean et al., 2020, 2021).

2. Theoretical background

2.1. International entry performance of digital products

Research on international market entry traditionally focuses on the determinants of entry mode (e.g., Anderson & Gatignon, 1986; Brouthers, 2002; Erramilli & Rao, 1993; Jell-Ojobor et al., 2022; Zhao et al., 2004), location (e.g., Agarwal & Ramaswami, 1992; Boeh & Beamish, 2012; Filatotchev et al., 2007), and timing choices (e.g., Kumar et al., 2020; Zhou & Wu, 2014). Most studies and theories are concerned with the physical, discrete entry by firms into a foreign country, assuming that entry performance depends on a suitable entry mode. Although there are some notable studies of post-entry performance, such as Buccieri and Park (2022), Donbesuur et al. (2022), and Piperopoulos et al. (2018), scholars tend to focus on the performance implications for the overall multinational enterprise, instead of entry performance in a particular target country. This prevents us from understanding what strategic factors will drive entry performance across different international markets.

By contrast, for digital products, the performance of a product in any given country is more readily accessible. Prior research highlights the importance of studying the actual market penetration of digital firms (Chen et al., 2019; Shaheer & Li, 2020) and the conditions under which digital firms can attain superior performance (Kapoor & Agarwal, 2017). In this research, we build upon those studies to examine the key strategic factors driving the entry performance of digital products.

2.2. Global competitiveness of digital freemium products

A unique feature of digital products is their instant access to international markets as most digital technologies are available around the world through digital channels since their inception (Banalieva & Dhanaraj, 2019; Coviello et al., 2017). Hence, the digital context is more aligned with Putsis' (1997) model where a product is introduced simultaneously to different countries. Still, the growth of digital technologies is not fundamentally different from that of tangible products as they organically diffuse across countries through a process of user adoption (Chen et al., 2019; Shaheer & Li, 2020). However, the ease of innovation and instant global availability results in stiff competition as thousands of firms release millions of digital products, preventing firms from differentiating their products against competitors and gaining sufficient user attention in various markets (Benner & Waldfogel, 2023; Boudreau, 2012). Hence, standing out from a sea of competing products becomes a crucial metric for international market entry.

We contend that current strategy frameworks about gaining a competitive edge through generic strategies may not help facilitate the internationalization of digital products. Generic strategies simplify a myriad of possible strategies into a limited set of strategy types, low cost and differentiation, which provide firm with distinct options for attaining a distinct competitive position; firms focusing on standardized but low-cost products spread around world through affordable prices, while firms focusing on differentiation fulfill specialized user needs across countries (Li et al., 2009; Porter, 1980; Roth & Morrison, 1992). However, launching digital products naturally entails low cost, enabling firms to offer novel digital functionalities addressing specialized user needs around the world through a freemium business model (Benner & Waldfogel, 2023; Rietveld, 2018). Hence, the trade-off between low-cost mass production and high-cost but differentiated specialization is no longer viable for digital freemium products, requiring a fresh perspective toward generic strategies and competitive positions in a digital age.

2.3. A demand-side perspective on competitive strategies of digital freemium products

We build on demand-side perspective (Priem, 2007; Priem et al., 2013; Shaheer & Li, 2020; Ye et al., 2012) to propose novel generic strategies from the demand side, suggesting that engaging with different users may provide novel positional advantages to improve entry performance of digital technologies. Demand-side perspective evaluates how product markets and consumers, rather than factor markets, resources, and firm capabilities, can provide a user-based competitive edge in both domestic and international settings (Siqueira et al., 2015; Zander & Zander, 2005). More specifically, it suggests that value creation is affected by users' perceived benefits from using the products and value capture is determined by users' willingness to pay (e.g., Rietveld, 2018; Sohl et al., 2020). Recent demand-side research (Ho-Dac, 2020; Shaheer & Li, 2020) further highlights the contributions users can make

to firms by sharing their ideas, developing new solutions through toolkit customizations, and spreading WOM across countries. As the seminal Bass model suggests, external influences, such as communications and advertising, as well as internal influences, such as social interactions between adopters, affect the likelihood of product adoption (Bass, 1969). While significant advertising investments may not be feasible for small digital firms, they may still rely on user communication.

We extend extant demand-side perspective research (e.g., Rietveld, 2018; Shaheer et al., 2020), which suggests that digital products can exploit and fulfill users' heterogenous preferences to increase their perception of value and willingness to pay. By serving heterogeneous customer needs, digital products can capture distinct competitive positions (Rietveld, 2018; Rietveld & Eggers, 2018), which in turn helps them generate more revenues when entering new markets. However, there is little understanding of specific demand-side competitive positions digital products can occupy in overseas markets. We use the novel context of digital freemium products to propose distinct demand-side positions that may help improve entry performance in overseas markets.

2.4. Network effects and WOM for digital freemium products

Digital freemium products are one of the most prominent business models in the digital age. Unlike premium products that require users to pay before experiencing any product benefits, freemium products do not require any upfront payments but charge users for add-on features (Tidhar & Eisenhardt, 2020; Varaiya, 2017). This temporal transaction decoupling decreases users' perceived benefits, resulting in a lower willingness to pay to use freemium products (vs. premium products) (Rietveld, 2018). Further, freemium products need to achieve a higher diffusion level than paid-only products to enhance their revenues (Rietveld & Ploog, 2022). To facilitate product diffusion, freemium products often incorporate social features (e.g., multiplayer functionality, chatting tools, and social media features) to reinforce the direct network effects (Agarwal et al., 2023; Dou et al., 2013). Social features can increase the potential network value of user interactions in addition to offering utilitarian or hedonic benefits. Moreover, compared to premium products, freemium products are more likely to encourage WOM by satisfied users because of the reciprocal behavior of users (Bond et al., 2019), lower risks to adoption (Rietveld & Ploog, 2022), and higher adoption probability by the receiver (Kamada & Öry, 2020). WOM reduces user uncertainty to facilitate the rapid diffusion of freemium products (Cheema & Kaikati, 2010; Yan et al., 2021). Therefore, leveraging network effects through the inclusion of social features and leveraging WOM via favorable user evaluations emerge represent two key factors that play a critical role in the subsequent performance of newly released digital products with freemium model (Miric & Jeppesen, 2020; Oh et al., 2016; Rietveld & Ploog, 2020).

An emphasis on the advantages of network effects and WOM, however, neglects the distinct demand-side logics that drive network effects and WOM for digital freemium products. Intuitively, network effects and WOM should mutually reinforce each other as freemium products with strong network effects should enjoy positive WOM referrals from satisfied users. However, prior research suggests that invoking network effects usually attracts large but diverse users with significant heterogeneity in their preferences and expectations (Guo & Zhang, 2012; Rietveld, 2018; Shaheer et al., 2020). For example, a recent study (i.e., Farronato et al., 2023) showed that promoting network effects of a freemium product had the unintended consequence of enhancing user heterogeneity, which subsequently led to a decrease in satisfaction among users whose needs were not fully met by the platform. It indicates that promoting network effects can compromise a digital freemium product's ability to generate WOM as the diverse preferences of heterogenous users are hard to satisfy (e.g., Gruca & Rego, 2005; Keiningham et al., 2014; Rego et al., 2013). Instead, a digital freemium product is more likely to generate WOM by satisfying similar preferences of smaller, more focused user segments to receive favorable user evaluations (e.g., Claussen et al., 2013; Keiningham et al., 2014; Onofrei et al., 2022; Rego et al., 2013).

The distinct logics of accumulating a heterogeneous userbase for network effects and satisfying a homogeneous userbase for WOM call for exploring more complex and multidimensional nuances underlying the performance of digital freemium products. It still remains unclear to what extent, network effects and WOM can contribute to the success of a new freemium product and the contextual conditions under which each of these different mechanisms will play a more salient role. The internationalization of digital freemium products presents a unique setting, enabling us to better distinguish the roles of network effects and WOM in affecting entry performance in different institutional contexts. Therefore, we investigate the distinct demand-side competitive positions that digital freemium products can attain by choosing between the strategies of fostering user interactions via incorporating social features and the strategies of delivering high user satisfaction.

3. Hypotheses

In this study, we follow recent research on digital freemium products (e.g., Boudreau et al., 2022; Rietveld, 2017; Tidhar & Eisenhardt, 2020) to use revenue generation for characterizing entry performance. Although virtual presence removes physical entry barriers and dampens liabilities of foreignness for digital businesses, it by no means guarantees higher revenues (Brouthers et al., 2022; Chen et al., 2019). We extend demand-side perspective to argue how social product features and product ratings influence value creation and value capture of freemium products in different demand environments. In particular, As there are two main sources of revenue for digital freemium products, advertising revenues and add-on sales (Guo et al., 2019; Hao et al., 2017; Tidhar & Eisenhardt, 2020), we explore the extent to which network effects and WOM can help increase revenues from advertising and add-on sales for newly released freemium products by addressing unique demand-side preferences of users across different institutional contexts. We present our conceptual model in Fig. 1.

3.1. Network effects

A product carries a network effect when the benefits that users derive from the product increase due to the rise in the number of users of the same product (e.g., Miric & Jeppesen, 2020; Oh et al., 2016; Shi et al., 2019). Existing studies have shown how product design may influence the intensity of network effects. For example, social features related to product design which are arranged to make it easier for users to socialize, will add network functionality to the products and strengthen the product-level network effects (Agarwal et al., 2023; Dou et al., 2013; Rietveld & Ploog, 2022). That is, social features, such as multi-player mode, messaging or chat tools, discussion forums, and social media features in mobile games, enable relationship building and interactivity among users and thus create additional value for users from playing and communicating with peers. Incorporating social features can cultivate network effects and increase the revenue generation of a new freemium

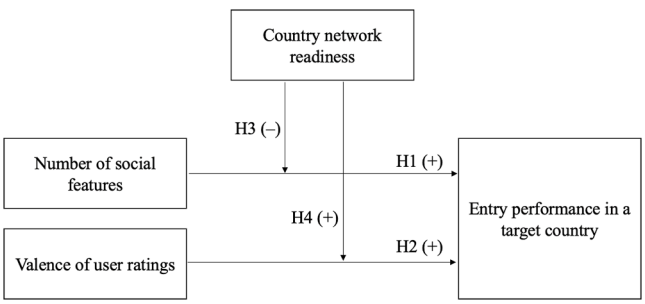

Fig. 1. Conceptual model and research framework.

product in two ways. It can boost the value of social interactions and the user base growth, thus improving advertising revenues. In addition, it can enhance connectivity between users and help take advantage of social influence, leading to increased users' willingness to purchase add-ons.

Referring to prior research on freemium, we note that freemium products require an accelerated diffusion process to enhance revenue performance (Boudreau et al., 2022; Cheng & Liu, 2012; Rietveld & Ploog, 2022). In this case, we suggest that freemium products with many social features may engineer the strength of network effects and attract more users than competitors without social features through increased utility derived from the userbase. The network functionalities support users' social interactions with peers and increase the information available for users, thus encouraging existing users to bring in new users, which may ultimately help to gain a relatively large base of users. Such large userbases may enhance advertising revenues of digital freemium products for two main reasons. First, advertisers are willing to pay high advertising rates for a product with a large userbase (Gal-Or et al., 2018; Kaiser & Wright, 2006). The massive userbase increases the value created by the product through consumption externalities, and high demand makes the product alluring to potential advertisers. Second, as it is difficult to convert users from free to premium, a larger userbase allows freemium products to generate more advertising revenue from reward ads that let users opt to either purchase add-ons or view ads in exchange for free items (Guo et al., 2019).

On the other hand, using freemium products with network value allows users to socially fit in with their peers or derive social prestige from using high-end premium items (Hamari et al., 2020; Shi et al., 2019). Digital products with social features may invoke bandwagon effects as users value psychological benefits accruing from adopting these products, leading to a "herding" behavior where new users learn from and imitate the observed behavior of previous adopters (Banerjee, 1992; Jang & Chung, 2021; Zhao et al., 2020). Network effects from social features may also enable social comparison and competition between users, hence improving the perceived social value of freemium products wherein users adopting them avoid feeling excluded and the fear of missing out on fads and fashions. Moreover, social functionalities provide an opportunity for users to raise their virtual social status via purchasing a premium version with enhanced features or even no functional purpose (Marder et al., 2019; Wang et al., 2022). Intuitively, mobile game players who buy a premium item need someone else to play with or to show off to (Wu et al., 2013). At the same time, users may continue playing and spend money on accessory items so as to proceed and keep up with fellow players (Hamari et al., 2020). Therefore, strong network effects created through social features may boost adoption rate of newly released freemium products and their paid items.

Taken together, we expect that implementing social product features and harnessing the ensuing self-reinforcing network effects will help freemium products grow revenues after entering target countries. Hence, we hypothesize that:

Hypothesis 1. Inclusion of social features by freemium products will increase entry performance in target countries.

3.2. WOM

WOM represents the act of users recommending products to other users, and is closely related to user satisfaction with a product (Babić Rosario et al., 2016; Filieri, 2015; Reuber & Fischer, 2009, 2011; Rietveld & Ploog, 2020; Taeuscher, 2019). In a digital era, the most prominent form of WOM is the online user rating through which users recommend a product to new users (e.g., Bond et al., 2019; Timmerman & Shepherd, 2016). Digital freemium products can easily incentivize satisfied users to generate positive WOM for two reasons. First, users may feel compelled to reciprocate, thus talking to new users (Bond et al., 2019; Lin et al., 2019). Second, users may also feel more comfortable recommending products that do not entail upfront monetary costs (Aydinli et al., 2014; Rietveld & Ploog, 2022).

We suggest that WOM, through positive user ratings, may contribute to the entry performance of freemium products by attracting users interested in the specialized features of the product, thus generating add-on sales. Mainly, freemium products successfully creating WOM may invoke substantial consumption complementarities by bringing together users with shared preferences (Casadesus-Masanell & Hałaburda, 2014; Fainmesser et al., 2021). It may create a virtuous circle as WOM may specifically attract users who are more likely to be satisfied with the products, which may further spread positive WOM to attract even more users. In this case, users have similar specific needs and are more inclined to pay for advanced and complex premium features that fit their preferences.

Furthermore, even though free users can learn about the product quality via their personal experience (Foubert & Gijsbrechts, 2016; Liu et al., 2014), they may perceive the benefits of the freemium product to be higher than the premium product because of zero-price effect or loss aversion (Biraglia et al., 2022; Gu et al., 2018; Koch & Benlian, 2017). Accordingly, positive WOM can not only help users reduce uncertainty about add-on product quality, but also improve their perceived product benefits (Foubert & Gijsbrechts, 2016), which leads to an increase in add-on sales.

However, WOM may have little effect on advertising revenues as many advertisers are less likely to focus on products catering to a small group of users (Babić Rosario et al., 2016; Ji et al., 2019; Moe & Trusov, 2011). On the other hand, these freemium products may continue attracting advertisers looking for more targeted advertising to users with similar needs and tastes (Schumann et al., 2014). Further, products focusing more on user satisfaction may avoid advertising as heavy advertising may easily overwhelm and irritate users (Martins et al., 2019).

In summary, improved user satisfaction and the diffusion of WOM can help freemium products earn revenue from add-on purchases but may have little or no effect on advertising revenues. Hence, we hypothesize that:

Hypothesis 2. A higher user rating by freemium products will increase entry performance in target countries.

3.3. The moderating role of country network readiness

Though we suggest that either network effects or WOM may contribute to the entry performance for digital freemium products, our theoretical arguments does not distinguish user preferences across different demand environments, which may affect the value users derive from either network effects or WOM. In particular, as freemium apps rely on digital infrastructure that ensures the seamless transfer of information and payments in a country, we draw attention to substantial variation across countries in terms of their network readiness (Anwar, 2018; Hoffman et al., 2013; Van Alstyne & Brynjolfsson, 2005), which is defined as the extent to which a country leverages digital technologies in economic and social lives (Baller et al., 2016).

Countries with high network readiness are characterized by a demand environment that grants people easy access to information and communication flows in cyberspace. It leads to higher user sophistication as users frequently rely on digital technologies to meet a large variety of needs. By contrast, the demand environment in countries with low network readiness imposes high costs to access usually unreliable digital infrastructure, which lowers public access to digitally available information sources and decreases reliance on digital technologies in daily lives (Baller et al., 2016; Shaheer et al., 2020). Elaborating on these differences from a demand-side perspective, we suggest that differences among countries with low and high network readiness may influence user responses to network effects and WOM, which may lead to variations in the effectiveness of incorporating social features or delivering

high user ratings across countries.

We suggest that demand conditions in countries with low network readiness may amplify the impact of social features on the revenue generation of digital freemium products. With lower access as well as trust in digitally available information, people are more relying on interpersonal communication and are susceptible to herding behavior as observing usage by peers may encourage them to use the same products (Bapna & Umyarov, 2015; Hung et al., 2011). Further, we argue that social interactions are more likely to enhance the perceived social value of freemium products in countries with low network readiness, where users may adopt digital technologies to fulfill their social needs rather than material needs. The pursuit of deepening social connections by adopting products with network functionality may substantially strengthen bandwagon effects (Chen et al., 2019), as users derive more utility from current networks instead of standalone features of freemium products. Indeed, reduced concern about product functionalities may enhance user tolerance for lower quality or extensive advertisements in a freemium product, as far as the product could deliver network value through social features. Such tendencies may further strengthen as less sophisticated demand conditions exist in countries with low network readiness where users focus on meeting generic needs through digital products. However, users in countries with high network readiness may anticipate less benefits from products that incorporate many social features because they extensively rely on digital infrastructure in every aspect of life, and thus have various personal specialized interests. In such countries, it may be essential to provide products focusing more on standalone functionality to satisfy users' preferences. Based on these arguments, we suggest that:

Hypothesis 3. A decrease in the network readiness of target countries will strengthen the effect of social features on entry performance.

On the contrary, we suggest that demand conditions in countries with high network readiness may strengthen the impact of WOM on add-on sales. In these countries, the ease and security of digital payments may enhance user willingness to purchase premium services to fulfill their needs or avoid advertising (Balakrishnan & Shuib, 2021). However, users in these counties are likely to be more sophisticated and seek cutting-edge products to fulfill their specific needs (Baller et al., 2016; Chakravorti et al., 2020; Shaheer et al., 2020). WOM, in this case, may play a more prominent role as higher ratings may signal the ability of a freemium product to successfully meet specialized user needs the product claims to address in its description or keywords (Hofstede et al., 2002; Rogers, 2003; Van Alstyne & Brynjolfsson, 2005). Accordingly, WOM of freemium products can help attract a niche but loyal userbase that may pay for the advanced features.

However, WOM may have a lower impact on add-on sales in low network readiness countries where the Internet is expensive relative to resident income, and users usually rely on low-cost and low-tech devices (Rodríguez-Castelán et al., 2021). As a result, users care less about sophisticated features and functionalities, which makes them less likely to pay for advanced features (Vimalkumar et al., 2021). Users in low-network countries may also be skeptical of the transparency and reliability of online WOM as they may suspect businesses of manipulating their ratings (Chakravorti et al., 2018). As a result, they may be reluctant to pay for advanced features despite high ratings. Based on these arguments, we hypothesize:

Hypothesis 4. An increase in the network readiness of target countries will strengthen the effect of user ratings on entry performance.

4. Data and methods

4.1. Data and sample

We use a sample of gaming apps in the Apple app store for empirical analyses. The category of gaming apps is highly appropriate to capture the distinctiveness of the app economy because games largely reach their users through digital channels without requiring any physical presence. Apps in other categories, however, may be relatively similar to more traditional businesses as they also offer offline components. Further, an overwhelming majority of games at the app store are free with no associated paid games, which allows us to conduct a more focused analysis of the dynamics of freemium products. At the same time, a study of gaming apps has implications for generalization because of the diverse range of subcategories within the gaming category. Apple app store offers 25 subcategories of gaming apps that target different user segments. Gaming is also the largest category of apps that experiences high growth along with an intensely competitive environment, providing suitable research setting for investigating research questions related to entry performance in international markets.

Empirically analyzing the gaming category at the Apple app store offers several advantages. Given various systematic differences across app categories and app stores, focusing on one category in a specific app store may mitigate the influence of such heterogeneity (Ghose & Han, 2014; Shaheer & Li, 2020). Another important advantage of our study is our focus on the Apple app store, one of the world's most prominent app platforms. More importantly, users on other app platforms, such as Google Play, can download the same apps from many different stores, which makes it impossible to track the performance of an app. Users cannot access iOS apps from platforms other than the Apple app store, and this helps more accurately track app performance in a country. Moreover, the Apple app store has a distinct feature of Game Center, which allows users to play with other users through multiplayer features and share their accomplishments on leaderboards. This creates a prominent channel for network effects, one of the metrics for superior performance of freemium products (Boudreau et al., 2022).

We acquire a proprietary database of freemium gaming apps available at the Apple app store. This dataset covers the daily performance of all gaming apps across 57 countries for two years, from 2016 to 2017. The app industry is highly skewed, where a small number of apps claim the overwhelming majority of users and revenues (Garg & Telang, 2013; Ghose & Han, 2014). Therefore, we follow Kapoor and Agarwal (2017) to construct a more manageable but also comprehensive sample of meaningfully performing apps. First, we generate a list of the top 1500 gaming apps in terms of revenues in each country on the 15th of each month. We only include those freemium apps in our sample which appear in top-grossing rankings at least three times. Our base sample consists of 7291 apps that earned more than 90 % downloads, ratings, daily active users (DAU), and revenues in the gaming category of the Apple app store during our study period. The sample includes a wide range of apps in terms of performance, including apps that accumulated millions of downloads and maintained top rankings in multiple countries for several months, as well as apps that never got ranked among the top 150 in any specific country and earned very few downloads globally. Second, we draw a sample of only newly launched apps so that we could track them since their inception. After removing apps with missing values against our main variables and control variables, the final sample comprises of 1137,625 monthly observations from 1891 freemium gaming apps followed in 57 countries from January 2016 to December 2017.

Our sample gaming apps are mainly from the following subcategories: Role Playing (24.74 %), Action (15.11 %), Strategy (14.01 %), Simulation (9.19 %), Adventure (6.08 %), Puzzle (5.77 %), Casino (4.33 %), Card (4.17 %), Sports (3.09 %), and Arcade (3.19 %). The target countries in our sample include 64.57 % of high-income countries, 22.34 % of upper-middle-income countries, and 13.09 % of lower-middle-income countries based on World Bank's country classification. These countries are also diverse in terms of network readiness, ranging from very high network readiness countries (e.g., Singapore, Finland, and, Sweden) to very low network readiness countries (e.g., Nigeria, Venezuela, and Egypt). Our unit of analysis is an individual gaming app. We track the performance of each app in every country as a function of

the social features (reflecting network effects) and app ratings (an indicator of WOM), given other controls. Unless stated otherwise, we convert daily indicators, such as daily ratings, to create monthly variables.

4.2. Measures

4.2.1. Dependent variable

Our dependent variable is apps' entry performance in a target country. Following prior research focusing on digital products (Boudreau et al., 2022; Ji et al., 2019; Kapoor & Agarwal, 2017), this was measured by the monthly revenue of a newly launched freemium app, earned from in-app purchases and in-app advertising, in a county. We use the natural logarithm of the revenue (plus 1) to account for the skewed distribution. The number of downloads is also a commonly used measure for app performance (van Angeren et al., 2022) and our results hold when adopting the count of downloads as an alternative measure.

4.2.2. Independent and moderating variables

Our first independent variable, *Social features*, is measured as the number of software development kits (SDKs) with social functionality that an app utilize in the month t-1. We follow the literature and capture direct network effects using product-level social features as a strong proxy (Agarwal et al., 2023; Boudreau et al., 2022; Rietveld & Ploog, 2022). The social product features in our dataset include multiplayer functionality, chatting tools, and social media features. The number of SDKs with social functionality reflects the levels of user interactions that users can fully experience when adopting an app. The apps incorporating many SDKs with social functionality may be more likely to benefit from direct network effects (Agarwal et al., 2023). We also assess the robustness of our results using alternative measurements, including the log-transformation of the number of social SDKs and a dummy variable indicating whether an app has any social SDKs; the results are consistent with the main findings.

We operationalize our second independent variable, *App ratings*, using average user ratings an app received in the target country in the month t-1. Apple app store allows users to rate an app on a scale of 1 (lowest) to 5 (highest). Most users refer to these ratings for guiding their decision about adopting an app (Chen et al., 2019; Kübler et al., 2018). As app ratings are prominently displayed on the Apple app store and substantially influence the adoption decisions of new users (Arora et al., 2017; Ghose & Han, 2014; Kapoor & Agarwal, 2017; Tidhar & Eisenhardt, 2020), they may reflect the most relevant indicator of WOM whose positive or negative tone may determine app adoption in a country. Prior research also suggests ratings as important indicators of WOM and the reputation of digital products like apps (e.g., Babić Rosario et al., 2016; Bond et al., 2019; Reuber & Fischer, 2009, 2011; Timmerman & Shepherd, 2016). Hence, the higher the ratings, the more positive the WOM an app generates.

Target country network readiness is our moderating variable. We obtain network readiness scores for each country from the network readiness index developed by the World Economic Forum in partnership with INSEAD and Cornell University. This is one of the most comprehensive indices evaluating 193 countries based on 53 individual indicators, including digital regulations, cost and affordability of digital technologies, skills of individual citizens, and the extent of the usage of digital infrastructure. Overall, this index provides a comprehensive view of each country based on both macro (regulations, the sophistication of digital infrastructure, etc.) and micro (cost, affordability, skills, and the intensity of using digital technologies, etc.) level indicators. This index is published every year for each country. As our study period is 2016–2017, we use 2015 network readiness scores for observations in 2016 and 2016 network readiness scores for observations in 2017.

4.2.3. Control variables

We follow the literature to control for the app-, publisher-, industry-, and country-level variables in our empirical model.

First, we control for app-specific variables. A*pp size* is measured in gigabytes as a proxy to reflect the sophistication and inherent quality of an app, as apps with larger sizes are likely to have more features and graphics (Ghose & Han, 2014; Shaheer & Li, 2020; Tidhar & Eisenhardt, 2020). *Multihoming* refers to the tendency of app developers to host apps on multiple platforms (Landsman & Stremersch, 2011). We control for multihoming through a binary variable which takes the value of 1 for each month in which an app was also available on google play. *Age restriction* is a binary variable that takes the value of 1 if the app is restricted for any age group.

Second, we control for app developer-specific variables. *App developer experience* controls for the prior experience of app developers. This is a time-varying measure of the number of apps a developer has launched before a particular month. Experience with more apps may provide important insights to app developers and may have important consequences for app performance. *App developer downloads* controls for the prior performance of an app developer in each target country. This is a country-level time-varying variable, measuring the total downloads of all apps of an app developer earned in the target country over the past 12 months.

Third, we control for industry/subcategory- and country-specific variables. *Subcategory size* controls for the total downloads earned by all apps in a subcategory in a target country each month. We use the complete dataset of 7291 apps to calculate this variable for every subcategory. This variable reflects the attractiveness of a target country with respect to the subcategory. A larger country market may also offer an open environment where many apps may coexist and succeed commercially. *Subcategory concentration* is a measure of the competitiveness of a subcategory. This is an entropy measure in which we sum the squares of download shares of all 7291 apps in each subcategory in each country. In highly concentrated subcategories, a few apps enjoy the most download shares, whereas subcategories with lower concentration accommodate a greater number of apps, each having a smaller market share. High concentration can be an important barrier for new entering apps. *Subcategory engagement* takes into account the interest of users in a subcategory in each target country. We calculate this time-varying variable by measuring the average number of users in each country who use apps in a subcategory daily in each month. We also include subcategory dummies to control for other subcategory-specific effects. *Target country population* is a country-level variable measuring the yearly population of each target country. We get this variable from World Bank Database.

4.3. Statistical approach

Our research identifies the impact of social features and user ratings on app entry performance in a target country. We follow previous studies on the performance effect of products in a mobile app market (Barlow et al., 2019; van Angeren et al., 2022) by using a generalized estimating equations (GEE) model that seeks to estimate the average response over the population. GEE panel data models are suitable for our analysis because they account for possible correlations in the data across time periods. We estimate the models using the *xtgee* procedure in Stata. We use the commonly employed Gaussian distribution as the distribution family of the GEE models because app performance is a continuous variable. In our analysis, we compute robust standard errors for all the estimations. We lag all independent variables and control variables by 1 month to mitigate concerns about the possibility of reverse causality.

5. Results

Table 1 reports descriptive statistics and correlations between variables. The results show that there is little correlation between variables. The VIF score ranges from 1.02 to 1.19, well below the threshold value of 10 (Neter et al., 1985). Therefore, multicollinearity does not cause a

Table 1
Descriptive statistics and correlations of variables.

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	VIF
1. Revenue	2.93	1.93													
2. Social features	0.81	1.03	0.036												1.05
3. App ratings	3.35	1.49	0.059	0.205											1.09
4. Target country network readiness	4.78	0.78	0.011	0.066	0.038										1.10
5. App size	0.29	0.33	0.039	−0.022	0.027	−0.004									1.03
6. Multihoming	0.33	0.47	0.072	0.058	0.168	0.004	−0.116								1.08
7. Age restriction	0.73	0.45	0.016	−0.051	−0.152	−0.0001	0.090	−0.196							1.08
8. App developer experience	36.61	94.85	0.008	0.0001	0.062	−0.001	0.016	0.084	−0.063						1.02
9. App developer downloads	1.50	14.03	0.045	0.003	0.038	0.025	0.047	0.029	−0.035	0.104					1.04
10. Subcategory size	0.23	1.44	−0.002	−0.005	0.002	0.023	0.021	−0.017	0.035	−0.008	0.102				1.11
11. Subcategory concentration	0.05	0.10	0.134	−0.016	−0.010	0.034	−0.040	0.010	−0.112	−0.004	0.014	−0.060			1.04
12. Subcategory engagement	1.64	2.93	−0.013	0.022	0.003	0.005	0.082	−0.029	0.085	−0.016	0.004	0.055	−0.125		1.03
13. Target country population	0.10	0.24	−0.003	−0.021	−0.003	−0.262	0.006	−0.009	0.003	−0.002	0.124	0.277	0.033	0.001	1.19

$N = 1137{,}625$. Correlations with an absolute value greater than 0.003 are significant at $p < 0.001$ (2-tailed).
Abbreviation: VIF, variance inflation factor.

major concern.

Table 2 presents the results for the GEE models. Model 1 contains our control variables, independent variables, and moderating variables. We then separately add the interaction terms to Model 2 and Model 3. Model 4 is the full model, including all variables and interaction terms.

We first discuss the impacts of our independent variables. In Model 1 in Table 2, we find that the coefficients of both social features ($\beta = 0.093$, $p = 0.000$) and app ratings ($\beta = 0.562$, $p = 0.000$) are positive and significant, indicating that a higher level of network effects and WOM may help an app achieve higher entry performance in target countries. Hence, hypotheses 1 and 2 are supported. The economic significance of these coefficients is also substantial. When all other variables are held at their means, one standard deviation increase in social features and app ratings improves app performance in a country by 9.58 % and 83.78 %, respectively.

Next, we discuss the results of interaction terms. As shown in Model 4 in Table 2, the coefficient of interaction between social features and target country network readiness is negative and significant ($\beta = -0.023$, $p = 0.000$). To better understand the nature of the interactions, we plot the effect of social features on app entry performance for high and low levels of target country network readiness. Fig. 2 suggests that social features have a stronger positive effect on app entry performance when target country network readiness is lower. Thus, we find support for hypothesis 3. Similarly, Model 4 in Table 2 shows a positive and

Table 2
Regression results of Longitudinal Model: impact of App ratings on app revenues.

Variables	Model 1		
	Coefficient	standard errors	*p*-values
Social features	0.093	0.004	0.000
App ratings	0.562	0.002	0.000
Target country network readiness	−0.001	0.006	0.864
App size	0.303	0.013	0.000
Multihoming	0.203	0.011	0.000
Age restriction	0.246	0.012	0.000
App developer experience	0.002	0.000	0.000
App developer downloads	0.005	0.002	0.002
Subcategory size	0.002	0.001	0.012
Subcategory concentration	0.310	0.024	0.000
Subcategory engagement	−0.005	0.000	0.000
Target country population	−0.091	0.022	0.000
Constant	−0.872	0.046	0.000
Control for app subcategory	Yes		
Control for month	Yes		
Observations	1137,625		
No. of apps	1891		
Wald χ^2	290,881.78		0.000

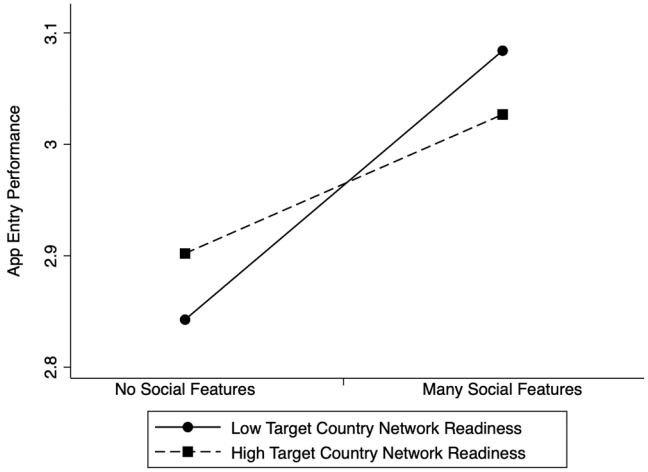

Fig. 2. Target country network readiness and network effects (social features)
Fig. 2 plots the moderating effect of target country network readiness on the relationship between apps' social features and entry performance based on results in Model 4 of Table 2. Apps with many social features indicate apps with social features above 75th percentile. Countries with network readiness above 75th percentile represent high network readiness countries and countries with network readiness below 25th percentile indicate low network readiness countries.

significant coefficient for the interaction between app ratings and target country network readiness ($\beta = 0.012$, $p = 0.000$). As shown in Fig. 3, the positive impact of user ratings on app entry performance amplifies under conditions of high target country network readiness. Therefore, hypothesis 4 is supported.

5.1. Robustness tests

To examine the robustness of our results, we conduct several additional tests as described below.

5.1.1. Difference between network effects and WOM

We empirically verify the different roles network effects and WOM play in generating revenue from advertising and add-on sales. We conduct another set of GEE panel regression models with robust standard errors, in which we separately regress in-app advertising revenue and in-app purchase on all independent and control variables. We present results in Table 3. Models 1 and 3 in Table 3 suggest significant and positive impact of social features on in-app advertising revenue ($\beta = 0.091$, $p = 0.000$) and add-on sales ($\beta = 0.072$, $p = 0.000$), which is consistent with our theoretical arguments that social functionalities lead to higher advertising revenues and in-app purchases. Models 2 and 4 further show negative and significant interaction terms between social features and network readiness ($\beta = -0.013, p = 0.001$; $\beta = -0.021, p = 0.000$), suggesting that low network readiness strengthens the effect of social features on advertising revenues and add-on sales. Moreover, Models 1 and 3 in Table 4 show that the effect size of the positive relationship between user ratings and in-app purchases (Model 3: $\beta = 0.547$, $p = 0.000$) is much greater than the influence of user ratings on advertising revenues (Model 1: $\beta = 0.124$, $p = 0.000$). It corroborates with our theoretical arguments that WOM is more likely to help generate revenues from add-on sales. Model 4 further shows a positive and highly significant coefficient for the interaction between user rating and network readiness (β=0.011, $p = 0.000$), indicating that high network readiness enhances the impact of WOM on in-app purchase revenues. Overall, these results provide support for our conjectures that network effects have positive impact on advertising revenue and add-on sales, whereas WOM is more strongly associated with add-on sales than advertising revenue.

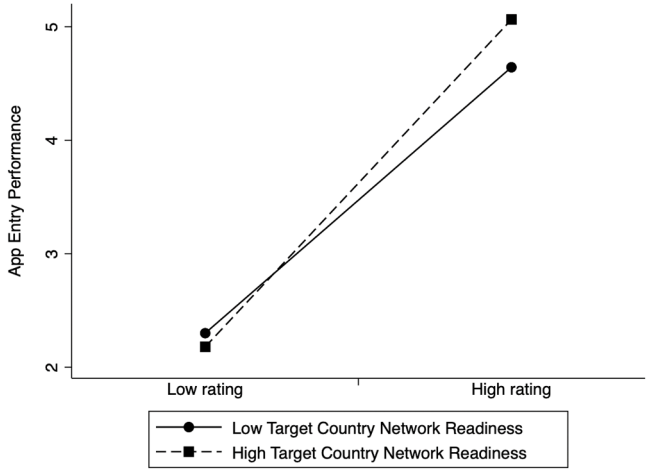

Fig. 3. Target country network readiness and word-of-mouth (app ratings)
Fig. 3 plots the moderating effect of target country network readiness on the relationship between app ratings and entry performance based on results in Model 4 of Table 2. Apps with high rating indicate apps with rating above 75th percentile whereas apps with low rating indicate apps with rating below 25th percentile. Similarly, countries with network readiness above 75th percentile represent high network readiness countries and countries with network readiness below 25th percentile indicate low network readiness countries.

We further validate our theoretical augments that apps leveraging network effects are more likely to accumulate more heterogeneous users whereas apps leveraging WOM may focus on satisfying the needs of relatively more homogeneous user segments (Gruca & Rego, 2005; Keiningham et al., 2014; Rego et al., 2013). We provide empirical evidence for this argument. Several studies (e.g., Moe & Trusov, 2011; Sun, 2012; Zimmermann et al., 2018) indicate that a higher variance in the rating of a product indicates higher heterogeneity in user preferences for the product, whereas a lower variance indicates greater similarity in preferences. Accordingly, we run a panel regression model with the variance of ratings as a dependent variable, measured as the standard deviation of ratings an app earns each month in a given country, and apps' social features and ratings as independent variables. We find a positive and statistically significant relationship between social features and variance of ratings, indicating that products with many social features may attract more heterogeneous users. On the contrary, we find a negative and significant relationship between app ratings and variance of ratings, implying that users of highly rated apps are more likely to exhibit similar preferences.

5.1.2. Robustness tests for main results

We perform several additional analyses. First, we use the fixed-effects and random-effects panel linear regression models with standard errors clustered at the app-country level in place of the GEE models to test for robustness. The results are reported in Table 4. Although we do not discuss these results, they are still consistent our main results that social features and user satisfaction lead to higher revenue performance, and a country's network readiness moderates these two relationships.

Second, we use alternate criteria for defining app entry performance in a target country as our main dependent variable. We estimate our models by using the downloads rather than revenue as a dependent variable. As shown in Table 5, the results exhibit similar patterns as our main results. We also use rating counts to measure of app entry performance and the results confirm out previously obtained results.

Third, we use alternate measures of our main explanatory variables to ensure that our results are not driven by specific operationalization of our variables. We re-run our models by using the log-transformation of the number of social SDKs and a dummy variable indicating whether an app has any social SDKs to assess the impact of network effects. We also operationalize app ratings as cumulative ratings that an app earned until month t-1. Furthermore, our moderator, target country network readiness, is a comprehensive index that combines 53 indicators into 10 pillars, which collectively determine the network readiness of a country. We estimate our model separately by replacing the target country network readiness with each of the 10 pillars. The results remain largely consistent under all these alternate specifications of our variables.

Fourth, we conduct two-stage instrumental variable regressions to check estimation biases from possible endogeneity of two main independent variables. We use average number of SDKs with social features in each app subcategory as an instrument for social features and average ratings in each subcategory as an instrument for app ratings. Following Wooldridge (2010), we include the interaction terms between instrumental variables and the moderating variable, target country network readiness, as additional instrumental variables. Our instruments are likely to affect social features and app ratings but unlikely to be related to the error term of an app's entry performance in a specific country. The results of our instrumental variable regression remain consistent with our main results.

Fifth, an important limitation of our study is our inability to control for the effects of the home countries of app developers and the distance between home countries of app developers and target countries. This is because our data provides home country information for only 400 app developers. While the app industry is largely global, where users rarely know the home country of app developers, differences across countries may still impact the potential of apps to achieve high entry performance in certain countries (Shaheer & Li, 2020). We partly mitigate this

Table 3
Regression results of generalized estimation equations models: impact of network effects and word-of-mouth on in-app advertising and in-app purchase revenue.

Variables	DV = in-app advertising revenue						DV = in-app purchase revenue					
	Model 1			Model 2			Model 3			Model 4		
	parameter Estimate	standard errors	p-values	parameter Estimate	standard errors	p-values	parameter Estimate	standard errors	p-values	parameter Estimate	standard errors	p-values
Social features	0.091	0.003	0.000	0.154	0.019	0.000	0.072	0.004	0.000	0.174	0.026	0.000
App ratings	0.124	0.001	0.000	0.068	0.007	0.000	0.547	0.002	0.000	0.496	0.015	0.000
Target country network readiness	−0.023	0.004	0.000	−0.049	0.005	0.000	0.005	0.006	0.468	−0.012	0.010	0.228
Social features x Target country network readiness				−0.013	0.004	0.001				−0.021	0.005	0.000
App ratings x Target country network readiness				0.012	0.001	0.000				0.011	0.003	0.000
App size	0.035	0.008	0.000	0.035	0.008	0.000	0.300	0.013	0.000	0.301	0.013	0.000
Multihoming	0.265	0.008	0.000	0.265	0.008	0.000	0.151	0.011	0.000	0.151	0.011	0.000
Age restriction	−0.148	0.009	0.000	−0.148	0.009	0.000	0.310	0.012	0.000	0.310	0.012	0.000
App developer experience	0.000	0.000	0.260	0.000	0.000	0.253	0.002	0.000	0.000	0.002	0.000	0.000
App developer downloads	0.002	0.001	0.008	0.002	0.001	0.008	0.005	0.002	0.002	0.005	0.002	0.002
Subcategory size	−0.001	0.001	0.055	−0.001	0.001	0.063	0.002	0.001	0.003	0.002	0.001	0.002
Subcategory concentration	0.261	0.022	0.000	0.261	0.022	0.000	0.278	0.024	0.000	0.278	0.024	0.000
Subcategory engagement	−0.004	0.001	0.000	−0.004	0.001	0.000	−0.002	0.000	0.000	−0.002	0.000	0.000
Target country population	−0.030	0.013	0.016	−0.030	0.013	0.017	−0.087	0.022	0.000	−0.087	0.022	0.000
Constant	−0.694	0.028	0.000	−0.569	0.031	0.000	−0.767	0.046	0.000	−0.684	0.060	0.000
Control for app subcategory	Yes			Yes			Yes			Yes		
Control for month	Yes			Yes			Yes			Yes		
Observations	1137,625			1137,625			1137,625			1137,625		
No. of apps	1891			1891			1891			1891		
Wald χ^2	50,685.10		0.000	50,700.24		0.000	297,452.37		0.000	293,351.99		0.000

limitation by running a shared frailty model to address the random effects and unobserved heterogeneity. We seek to further mitigate this issue by adding several developer-level and target country-level control variables. As a robustness test, we construct a reduced sample of only apps for which we have data about the home countries of app developers. We estimate our model on this reduced sample while controlling for the psychic distance between the home countries of app developers and each target country. We use the psychic distance index developed by Dow and Karunaratna (2006), which measures the psychic distance between each country dyad with regard to language, education, industrial development, religion, and political system. Despite the reduced sample, our results stay robust.

Finally, we follow Shaver (1998) to test our hypotheses by splitting the sample instead of using interaction terms. One sample only includes observations in which apps had many social features, and the other sample includes only observations in which apps had no social features. We compare the coefficients of target country network readiness in both samples and find patterns similar to our main results. We also split the sample with respect to app ratings following the same approach and find consistent results.

6. Discussion

6.1. Theoretical implications

Our study adds to research on international market entry in the digital economy by examining the entry performance of digital products with freemium models. Previous research in the IB literature has primarily focused on entry mode and location choices. However, where to enter and how to enter are not critical issues for digital products that have instant access to global users (Brouthers et al., 2022; Chen et al., 2019; Shaheer & Li, 2020). Therefore, entry strategy plays a less salient role since foreign entry barriers on app stores are intentionally lowered by platforms. Moreover, as the cost of downloading an app is minimal, digital internationalization may not be restricted by "information-revealing" effect, which reduces risk and uncertainty about more traditional products such as consumer durables (Takada & Jain, 1991; Terlaak & King, 2007). As recent studies explicitly suggest, the development and widely adoption of emerging digital technologies have disrupted the international competition landscape and fundamentally transformed business models in IB (Bohnsack et al., 2021; Jean & Kim, 2020; Jean et al., 2020, 2021; Jeong et al., 2022). We further develop this view by focusing on the more relevant issue for digital products, the entry performance. Our findings contribute to the nascent understanding of international market entry performance in digital freemium product settings, as freemium has become a popular business model for digital products (Boudreau et al., 2022; Rietveld & Ploog, 2022; Wang et al., 2022).

In addition, we extend demand-side perspective to shed new light on the burning issue of attaining global competitive advantage in the modern app economy by proposing two different paths digital freemium businesses can leverage for entry performance. Moving away from traditional resource-based advantages, we argue that digital freemium products can derive unique demand-side advantages by strategically engaging users in different demand environments, which may help them acquire distinct competitive positions. Such a distinction is akin to

Table 4
Robustness check: results of fixed-effects and random-effects panel regression models.

Variables	Fixed-effects models						Random-effects models					
	Model 1			Model 2			Model 3			Model 4		
	parameter Estimate	standard errors	p-values	parameter Estimate	standard errors	p-values	parameter Estimate	standard errors	p-values	parameter Estimate	standard errors	p-values
Social features	0.089	0.004	0.000	0.189	0.026	0.000	0.094	0.004	0.000	0.207	0.025	0.000
App ratings	0.550	0.003	0.000	0.483	0.016	0.000	0.565	0.002	0.000	0.509	0.015	0.000
Target country network readiness	−0.036	0.072	0.610	−0.071	0.073	0.325	0.001	0.006	0.867	−0.018	0.010	0.078
Social features x Target country network readiness				−0.020	0.005	0.000				−0.023	0.005	0.000
App ratings x Target country network readiness				0.014	0.003	0.000				0.012	0.003	0.000
App size							0.307	0.013	0.000	0.307	0.013	0.000
Multihoming							0.204	0.011	0.000	0.204	0.011	0.000
Age restriction							0.248	0.012	0.000	0.248	0.012	0.000
App developer experience	0.006	0.001	0.000	0.006	0.001	0.000	0.002	0.000	0.000	0.002	0.000	0.000
App developer downloads	0.005	0.002	0.005	0.005	0.002	0.005	0.005	0.002	0.001	0.005	0.002	0.001
Subcategory size	0.002	0.001	0.002	0.002	0.001	0.002	0.002	0.001	0.018	0.002	0.001	0.015
Subcategory concentration	0.313	0.025	0.000	0.313	0.025	0.000	0.309	0.024	0.000	0.308	0.024	0.000
Subcategory engagement	−0.005	0.000	0.000	−0.005	0.000	0.000	−0.005	0.000	0.000	−0.005	0.000	0.000
Target country population	−1.613	0.944	0.088	−1.919	0.947	0.043	−0.090	0.021	0.000	−0.090	0.021	0.000
Constant	0.693	0.351	0.049	0.890	0.356	0.012	−0.876	0.045	0.000	−0.786	0.058	0.000
Control for app subcategory	No			No			Yes			Yes		
Control for month	Yes			Yes			Yes			Yes		
Observations	1137,625			1137,625			1137,625			1137,625		
No. of apps	1891			1891			1891			1891		
R^2	0.249			0.239			0.398			0.398		

generic growth strategies for freemium products—in a similar manner to Porter's (1980) seminal conceptualization—but with important differences. Achieving cost leadership to compete on prices is less relevant for the freemium model. The alternative scheme is to take advantage of the freemium model by incorporating social features to enable user interactions and invoke network effects (e.g., Agarwal et al., 2023; Boudreau et al., 2022; Rietveld & Ploog, 2022). While it may lead to winner-take-all markets where digital businesses join the race to acquire the mass market of users, the ease of creating and distributing freemium products may also provide a conducive environment to breed the long tail of highly satisfied users (Brynjolfsson, Hu & Smith, 2010, 2011). Accordingly, we propose an alternate, but often overlooked, mechanism of breeding cults and starting positive cascades to create WOM within well-targeted user segments. Our conceptualization challenges the implicit assumption about the advantages of network effects and WOM as we extend Porter (1980) in a digital age to argue that both paths may help achieve success, though an equal emphasis on both metrics may stuck digital businesses in the middle; digital businesses may either fail to achieve largely incompatible goals or stay vulnerable to competitors focusing on one path. We do recognize that the network effects and WOM are not completely exclusive; leveraging network effects may still require a reasonable level of user satisfaction, whereas a focus on WOM may also require targeting a sizable niche. It indicates that the choice between network effects and WOM is a problem of degree as digital businesses need to decide the path that should be prioritized more (Cennamo & Santalo, 2013). Nevertheless, we draw attention to differences in demand environments across countries, suggesting that leveraging network effects or WOM can lead to variations in entry performance in different countries.

Furthermore, we extend the demand-side perspective to shed novel light on freemium product research. While a distinctive aspect of business model research is its emphasis on creating value for users, Priem et al. (2018) argue that business model literature pays little attention to the implications of the demand environment for creating and enhancing value for users. The demand-side perspective can enrich business model research by contributing a more granular understanding of value creation in different demand environments and for different user segments (Priem, 2007; Priem & Butler, 2001; Priem et al., 2013; Ye et al., 2012). Our paper underscores the implication of varying user preferences for the freemium model as we reconcile the effects of network effects and WOM on the freemium model success by identifying the demand conditions in which each metric is more likely to contribute to the performance of digital freemium products. We show that the effectiveness of network effects and WOM varies based on user preferences across countries, such that they may improve the performance of the freemium model in some institutional contexts while reducing the fit of freemium products with others. Hence, we highlight institutional boundaries of network effects and WOM, suggesting that the choice between network effects and WOM is not only a matter of strategic choice, but also a function of demand conditions in target markets.

Finally, we introduce network readiness as a novel dimension to systematically characterize demand environments of countries in the context of modern digital economy. While economic and cultural factors are still important for international management, digital businesses need to consider the presence of complementary infrastructure that facilitates the transmission of information about relevant digital technologies to users, enabling users to adequately experience digital technologies, and shape user preferences (Hoffman et al., 2013; Van

Table 5
Robustness check of the alternative measures (DV=downloads).

Variables	Model 1			Model 2			Model 3			Model 4		
	parameter Estimate	standard errors	*p*-values	parameter Estimate	standard errors	*p*-values	parameter Estimate	standard errors	*p*-values	parameter Estimate	standard errors	*p*-values
Social features	0.011	0.001	0.000	0.026	0.005	0.000	0.011	0.001	0.000	0.030	0.005	0.000
App ratings	0.028	0.000	0.000	0.028	0.000	0.000	0.010	0.003	0.000	0.009	0.003	0.001
Target country network readiness	0.062	0.003	0.000	0.064	0.003	0.000	0.050	0.003	0.000	0.053	0.003	0.000
Social features x Target country network readiness				−0.003	0.001	0.001				−0.004	0.001	0.000
App ratings x Target country network readiness							0.004	0.001	0.000	0.004	0.001	0.000
App size	0.035	0.006	0.000	0.035	0.006	0.000	0.035	0.006	0.000	0.035	0.006	0.000
Multihoming	0.064	0.005	0.000	0.064	0.005	0.000	0.064	0.005	0.000	0.064	0.005	0.000
Age restriction	−0.055	0.006	0.000	−0.055	0.006	0.000	−0.055	0.006	0.000	−0.055	0.006	0.000
App developer experience	0.0002	0.000	0.000	0.0002	0.000	0.000	0.0002	0.000	0.000	0.0002	0.000	0.000
App developer downloads	0.014	0.000	0.000	0.014	0.000	0.000	0.014	0.000	0.000	0.014	0.000	0.000
Subcategory size	0.005	0.000	0.000	0.005	0.000	0.000	0.005	0.000	0.000	0.005	0.000	0.000
Subcategory concentration	0.337	0.008	0.000	0.337	0.008	0.000	0.337	0.008	0.000	0.337	0.008	0.000
Subcategory engagement	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000
Target country population	0.241	0.009	0.000	0.240	0.009	0.000	0.241	0.009	0.000	0.241	0.009	0.000
Constant	−0.534	0.086	0.000	−0.544	0.086	0.000	−0.481	0.087	0.000	−0.490	0.087	0.000
Control for app subcategory	Yes			Yes			Yes			Yes		
Control for month	Yes			Yes			Yes			Yes		
Observations	1137,625			1137,625			1137,625			1137,625		
No. of apps	1891			1891			1891			1891		
Wald χ^2	56,626.33		0.000	56,637.00		0.000	56,678.40		0.000	56,696.05		0.000

Alstyne & Brynjolfsson, 2005). These differences may cultivate demand environments where users drive value from different sets of strategic factors. As our results indicate, the state of digital infrastructure can be a critical determinant for the entry performance of freemium model. Hence, we stress the need for exploring novel institutional dimensions, particularly from a demand-side, that are more relevant to internationalization in the digital landscape.

6.2. Managerial implications

Our research entails important implications for digital businesses seeking success through freemium model in overseas markets. First, despite substantial interest in the freemium model, current research pays limited attention to the international aspect of the freemium model. We suggest that freemium model can substantially improve the global prospects of digital businesses. By reducing the price barrier, freemium model may help digital businesses overcome the uncertainty that prevents the outright purchase of foreign and less familiar digital technologies, which may spur the trial and ultimately the adoption of digital technologies across countries.

Second, there is little understanding of the key factors digital businesses can leverage to achieve international success via freemium model. While current research recognizes the importance of network effects and/or WOM (e.g., Boudreau et al., 2022; Cheng et al., 2015; Dou et al., 2013; Gu et al., 2018), the extent to which these metrics can contribute to success across substantially different demand environments across countries is unclear. This is a critical issue as researchers (e.g., Kübler et al., 2018; Shaheer & Li, 2020; Stallkamp & Schotter, 2021) indicate that the world is yet far from becoming a global village despite recent advances in digitalization; substantial cultural, economic, and technological differences exist across nations what digital firms need to take into consideration. Extending these insights, we suggest that the recipe for success with the freemium model may not be the same across countries. Instead, digital businesses need to make strategic choices to improve the fit of their products with demand environments in target countries. Our recommendations may be particularly critical for resource-constrained digital businesses as we suggest ways for efficiently pursuing international success with lower costs by strategically choosing between investing in social features and investing in quality for WOM.

6.3. Limitations and future research

We acknowledge certain limitations of our study, which also open venues for future research. Mainly, our study evaluates the impact of network effects and WOM on the entry performance of premium digital products. An equally interesting area of enquiry is to evaluate whether and under which conditions digital businesses pursue a certain strategy. Also, our research measures entry performance through revenue across several countries, but digital businesses also face challenges related to user loyalty and retention. We hope future research will evaluate these important performance indicators. Finally, we cannot observe the individual users' characteristics in our dataset, such as hobbies, Internet experience, purpose of adopting gaming apps, etc. Thus, we focus on the country-level differences in network readiness that influence users' tendency to value social networks and online WOM. This nonetheless has implications for future research to look more deeply into the user characteristics that shape the impact of network effects and WOM on the entry performance of digital freemium products.

7. Conclusion

Our study ties to the research on non-traditional international market entry of digital products, deepening the research on digital freemium products by highlighting different strategic paths for entry success in different demand environments. We conduct our research in the novel context of mobile gaming apps at the Apple app store where digital freemium products dominate. In such a competitive context, what matters more is the extent to which an app can outgrow others by generating higher revenues in foreign countries. We investigate two pathways through which apps may achieve this objective, network effects via incorporating social features and WOM through generating high user ratings. Our findings suggest that both metrics facilitate app entry performance, but they are affected variedly by demand conditions across countries; countries with high network readiness strengthen the role of WOM but not the network effects. These findings extend the demand-side perspective to shed new light on entrepreneurial success through freemium business by distinguishing the mechanisms underlying network effects and WOM and by providing specific directions for aligning both metrics with the demand conditions of a target country. Our study thus shows that traditional wisdom can be extended to offer new venues for theoretical advancements and meaningful recommendations to practitioners. Our study will further motivate IB research on the nexus of the demand-side perspective in the burgeoning context of the modern digital economy.

CRediT authorship contribution statement

Noman Shaheer: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Liang Chen:** Writing – review & editing, Writing – original draft, Conceptualization. **Jingtao Yi:** Supervision, Software, Resources, Project administration, Investigation, Conceptualization. **Sali Li:** Supervision, Software, Resources, Formal analysis, Data curation. **Huiwen Su:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

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