Research article

Efficiency Assessment of Digital and 'Phygital' Food Retailers through Data Envelopment Analysis

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Abstract The food retail landscape has undergone significant transformation in recent years, driven by the rapid expansion of online shopping and shifts in internal and external environments. This change has catalyzed the growth of pure-play digital food retailers and the adoption of a 'phygital' (physical and digital) approach by modern retailers. Using Data Envelopment Analysis (DEA) and Tobit model, this study evaluated the efficiency of digital (n=17) and phygital (n=42) food retailers across different regions and the key factors contributing to their efficiency. Digital food retailers were slightly more efficient than their phygital counterparts. Financial, structural, and macroenvironmental variables influence online retail efficiency, with farmer partnerships emerging as a critical factor for enhancing performance. Structural and financial factors showed the importance of experience, strong supplier relationships, and cost-control strategies in creating more efficient retail systems. Interestingly, macroenvironmental factors, such as high internet penetration rates, impeded efficiency, while a nation's overall network readiness showed no significant influence.

Keywords e-commerce, online retail, omnichannel, efficiency

INTRODUCTION

The food retail industry has undergone a dramatic transformation in recent years, particularly following the pandemic, which accelerated the shift toward online shopping. As consumer behavior has evolved, online food retailing has become increasingly competitive, with companies striving to meet the demand for convenience, variety, and speed. The rapid rise of e-commerce in the food sector has pushed retailers to focus on operational efficiency and reconsider their structural strategies to remain competitive. This shift has highlighted the importance of integrating both digital and physical channels, known as omnichannel or phygital retailing, where seamless customer experiences are prioritized across all touchpoints (Piotrowicz and Cuthbertson, 2014).

In this highly competitive landscape, factors influencing operational efficiency, such as cost control variables, are inherently critical. However, the importance of structural strategies, particularly partnerships between modern retailers and small-scale farmers, has gained prominence. Collaborating with farmers allows retailers to cater to the market's needs as concerns about health, food security, and social and environmental issues arise (Slamet et al., 2020). The pandemic exposed vulnerabilities in global supply chains, allowing retailers to rethink their sourcing and partnership models.

The efficiency of online food retail is influenced by both internal and macroenvironmental factors, with varying levels of adoption across countries. For example, in European nations such as Norway, Sweden, and Finland, there has been significant growth in online food retail, driven by high levels of internet penetration and robust e-commerce infrastructure (World Bank, 2024; Portulans Institute, 2024). These factors are worth noting in response to online retail efficiency. Given the limited empirical evidence on efficiency benchmarks for both digital and phygital retail models, this study endeavors to identify both internal and external factors for retailers to maintain competitiveness in an increasingly dynamic market.

OBJECTIVE

This study aims to assess the efficiency of digital and phygital food retailers globally. It focuses on evaluating and comparing the efficiency of the two retail models and identifying the financial, structural, and macroenvironmental factors that influence their efficiency.

METHODOLOGY

This study utilized secondary data from S&P Capital IQ, reflecting current and real-world financial data from both public and privately held companies (Beauchamp et al., 2019). The data were screened to include global online food retailers. From an initial list of 1,712 companies, 59 were selected for further analysis based on the availability of financial data from 2019 to 2023 and their consistent focus on online food retail. These were categorized into digital (n=17) and phygital (n=42), the latter combining online and physical stores.

Data Envelopment Analysis (DEA) was conducted to evaluate the efficiency and performance of decision-making units (DMUs) across multiple inputs and outputs using the CCR model by Charnes et al. (1978), the BCC model by Banker et al. (1984), and the scale efficiency (SE) model. Following this, Tobit regression was performed to identify the factors influencing efficiency in online food retailing.

RESULTS AND DISCUSSION

Variable Selection for DEA

The selection of input and output variables for efficiency estimation must be aligned with the research context and operational characteristics of the decision-making units (DMUs). Following prior research on food retailing across both traditional and digital channels, as summarized in Table 1, this study employs four input variables: number of employees, assets, liabilities, and operating expenses. Revenue was used as the sole output variable.

Table 1 Previous evidence on the efficiency estimation in related domains

Author(s)	Research domain	DMUs	Input variables	Output variables
Sellers-Rubio and Mas-Ruiz (2006)	Supermarket chains	100	(1) Employees (2) No. of outlets (3) Capital (equity, debt)	(1) Revenue (2) Net income
Gupta and Mittal (2010)	Food and grocery retail outlets	43	(1) Total area of the store (2) Total no. of SKUs (3) No. of POS machine (4) Labor cost (5) Employees (6) Working hours	(1) Sales (2) Customer conversion ratio
Wang et al. (2020)	E-commerce	10	(1) Assets (2) Liabilities (3) Equity	(1) Revenue (2) Net income
Zheng and Khan (2021)	E-commerce	65	(1) Total assets (2) Total operating cost (3) Employees	(1) Revenue (2) Net income

Source: Author's compilation

Descriptive Statistics

Table 2 reveals significant differences between phygital and digital food companies. Phygital retailers have significantly higher labor forces and variability in assets, liabilities, and operating expenses. Similarly, it reported higher average revenue than digital companies, reflecting their larger scale and operational scope.

Table 2 Descriptive statistics of the variables (2019-2023)

Variables	Phygital (n=42)				Digital (n=17)			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Employees	26	385,250	77,987	98,721	24	18,834	3,232	5,602
Assets	290.74	84,987.86	13,691.94	19,983.97	0.53	5,114.60	617.04	1,230.96
Liabilities	124.04	62,413.78	9,909.20	14,840.01	0.21	3,046.52	370.96	737.08
Operating cost	854.74	86,424.66	16.830.04	21,774.39	0.73	3,506.50	788.12	1,105.12
Revenue	1,082.56	90,334.46	19,172.65	24,864.79	0.82	3,159.84	687.52	1,011.76

Note: Units are expressed in USD million except for number of employees in absolute value

Estimation of Efficiency

The DEA was performed to assess efficiency and performance across multiple inputs and outputs of the decision-making units (DMUs). There are two (2) common approaches to modeling efficiency: CCR and BCC. The BCC model assumes variable returns to scale, given by Eq. 1.

$$max\, z_0 = \theta + s_r^+ + \varepsilon \sum_{i=1}^{m} s_i^- \quad (1)$$

where

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{r0}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \theta y_{i0}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

Here, θ represents the efficiency score of the analyzed unit. A DMU is deemed efficient if $\theta = 1$ and all slack variables are equal to zero.

Given that the data were collected at the onset and during the pandemic, food retailers likely experienced both expanding and downsizing their operations to adapt to market demands—such as over 70,000 store closures from 2019 to 2023 and the notable growth of online retailing (Centre for Retail Research, 2024). Consequently, this study adopts scale efficiency (SE) as the most appropriate model to account for these operational changes (Dellnitz et al., 2018).

SE estimated by removing the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$, resulting in the CCR model (Charnes et al., 1978). As CCR efficiency scores are always less than or equal to BCC scores, SE is defined by Eq. 2.

$$SE_i = \frac{\theta^*_{CCR}}{\theta^*_{BCC}} \quad (2)$$

If $SE_i = 1$, the analyzed DMU operates at scale efficiency. Conversely, if $SE_i < 1$, it indicates the presence of scale inefficiencies.

Tables 3 and 4 present the efficiency results for the top digital and phygital food retailers from 2019 to 2023, with the digital retailers having an average SE of 0.8767 and the phygital retailers slightly lower at 0.8696. Both groups operate close to the optimal scale, but digital retailers show a slightly better ability to optimize their scale of operations. These findings support previous research suggesting that pure-play digital businesses achieve higher efficiency because of lower operational costs (Li and Chen, 2010).

Table 3 Results of the top 5 most efficient digital food retailers (2019-2023)

Retail name	Headquarter	Year	CCR	BCC	SE
ACL	United Kingdom	2000	1.0000	1.0000	1.0000
ORD	Japan	1997	0.7175	0.7177	0.9997
OCD	United Kingdom	2000	0.3662	0.3665	0.9992
EBH	China	2005	0.4540	0.4547	09985
ODA	Norway	2013	0.4563	0.4572	0.9980
Mean (n=17)			0.5482	0.6253	0.8767

Phygital retailers show a greater number of players operating at scale efficiency, whereas only one digital retailer achieves full scale efficiency. This suggests that phygital retailers have more flexibility in optimizing their scale despite the disruption caused by the pandemic.

Table 4 Results of the most efficient phygital food retailers (2019-2023)

Retail name	Headquarter	Year	CCR	BCC	SE
CSA	France	1959	1.0000	1.0000	1.0000
ASL	India	2000	1.0000	1.0000	1.0000
KMO	Finland	2004	1.0000	1.0000	1.0000
LCO	Mexico	1930	0.7092	0.7092	1.0000
VSM	United States	1937	0.6876	0.6876	1.0000
SPI	China	2001	0.6349	0.6349	1.0000
CBC	Brazil	1954	0.5574	0.5574	1.0000
Mean (n=42)			0.6510	0.7486	0.8696

Evaluation of the Variables Influencing Efficiency

The analysis then employs a Tobit regression model to identify factors influencing efficiency in online food retail, using financial indicators such as fixed assets and selling, general, and administrative (SG&A) costs; structural factors including years in business, number of stores, and explicit farm partnerships; and macroenvironmental indicators like the Network Readiness Index, which assesses digital technology capabilities across 133 economies (Portulans Institute, 2024), and the internet penetration rate, reflecting household telecommunication access (World Bank, 2024). The network readiness index evaluates a country's digital readiness across four pillars: technology, focusing on infrastructure and access; people, measuring information technology skills and usage; governance, assessing policies and digital trust; and impact, analyzing social, economic, and environmental outcomes. The Tobit model, in which the efficiency scores from DEA are used as the dependent variable, is described by Eq. 3.

$$Eff_{it} = C + \alpha_1 FA_{it} + \alpha_2 SGA_{it} + \alpha_3 YR_{it} + \alpha_4 STR_{it} + \alpha_4 FP_{it} + \alpha_5 NRI_{it} + \alpha_5 IP_{it} + \varepsilon_{it} \quad (3)$$

Where C represents the constant term, whileα_1,..., α_5 are the regression coefficients for each variable. $\varepsilon_{it}$is the error term, where *I* denote the company number (i = 1, ..., 59), and *t* for the time period from 2019 to 2023). Furthermore, multicollinearity among the variables was assessed using the Variance Inflation Factor (VIF), with all values remaining below 3.0, well within the suggested threshold of 5.0 (Hair et al., 2019). This confirms the absence of multicollinearity in this study.

The results presented in Table 5 highlight the multifaceted nature of efficiency determinants for retailers, with both financial and structural variables playing a significant role. The positive impact of fixed assets (β = 0.00110) suggests that investments in infrastructure, technology and other tangible resources contribute to improved operational efficiency. Conversely, higher SG&A costs (β = -0.27109) are associated with reduced efficiency, indicating that excessive overhead expenses and suboptimal resource allocation can hinder performance.

Structural variables such as years in operation (β = 0.00111), physical stores (β = 0.00001), and farmer partnerships (β = 0.11855) positively influenced efficiency, underscoring the importance of experience and collaborative value chain relationships. Years in operation reflect accumulated knowledge and operational refinement, while physical stores enhance customer reach and provide integrated online-offline experiences, such as home delivery or curbside pick-up strategies during the pandemic that offer unparalleled convenience to consumers (Li and Fisher, 2022). Farmer partnerships emphasize the advantages of stronger supplier relationships, enabling farmers to mitigate market risks and reduce transaction costs (Mangala and Chengappa, 2008). As such, it has helped retailers ensure product quality, reduce wastage, and stabilize value chains (Chengappa et al. 2016). This finding could guide reforms to integrate farmers into the food retail chain and foster a more sustainable and efficient supply system.

Interestingly, internet penetration (β = -0.00484) has a negative relationship with efficiency, which may be due to higher competition in areas with widespread internet access or inefficiencies in adapting to market demands in these environments. The lack of significance for network readiness suggests that while the technological infrastructure implemented by each country might be crucial, its direct effect on efficiency may be mediated by other inherent factors, such as the managerial capabilities or market strategies of the retailers.

Table 5 Results of Tobit regression (n=59)

Variables	β	Std. Error	z Value	Sig.
Fixed asset	0.00110	0.00051	2.15605	*
Selling, general, and administrative cost	-0.27109	0.12845	-2.11058	*
Years in operation	0.00111	0.00046	2.44264	*
Stores (Phygital = 1; digital = 0)	0.00001	0.00000	2.17312	*
Farmer partnership (with = 1; without = 0)	0.11855	0.03966	2.98930	**
Network readiness index	0.00451	0.00343	1.31426	
Internet penetration	-0.00484	0.00225	-2.15038	*
Constant	0.68957	0.16388	4.20765	***

*Note: Significant levels are shown as follows: *p < .05, **p < .01, ***p < .001; Log likelihood = 36.444; Wald statistic = 57.814;* R^2 *= 0.495*

CONCLUSION

Digital retail models have proven to be marginally more efficient than their phygital counterparts, particularly in light of significant scaling activities from 2019 to 2023. During this period, digital retailers benefitted from streamlined operations, reduced overhead costs, and enhanced supply chain efficiencies, all of which were more readily achieved in a fully digital environment. Key contributors to this efficiency include lower administrative and operational expenses, the absence of costs associated with physical store maintenance, and agility afforded by technology-driven processes.

Simultaneously, structural and relational factors, such as years in operation and partnerships with farmers, play a crucial role in boosting efficiency across both digital and phygital models. These factors highlight the importance of experience and strong supplier relationships in creating more efficient retail systems. Therefore, phygital retailers do not lag far behind digital retailers' efficiency due to their business tenure and scale of operations through their expansive physical networks.

Developing competitive strategies for highly penetrated markets, such as personalization, exclusive offerings, and active customer engagement, may effectively mitigate inefficiencies caused by market saturation and intense competition. Despite the network readiness of a nation in terms of its overall digital infrastructure, it did not contribute to online food retail efficiency.

Further studies comparing retailers by geographic scope could also offer a more granular understanding to identify localized strategies for improvement and analyze efficiency trends over time as digital and phygital retailers continue to scale and adapt to market dynamics, particularly in post-pandemic settings.

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