Controlling the Board: A Spatial Interaction Framework for Store-Level Market Potential in Retail IS

Clemens Brackmann[1[0009-0002-6667-0165]]

[1] University of Duisburg-Essen, Essen, Germany
clemens.brackmann@uni-due.de

Abstract. Accurate estimation of store-level market potential is a critical capability for retail information systems supporting pricing, assortment, and replenishment decisions. Yet existing approaches typically rely on static demographic proxies that fail to capture the competitive dynamics and spatial consumer behaviour shaping actual store demand. This paper proposes a conceptual framework for estimating store-level market potential in geographically bounded local markets under limited availability of competitor sales data. Building on a localized adaptation of the Huff model, the framework integrates store attractiveness, consumer travel behaviour, and spatial demand distributions to approximate the potential customer volume a store can realistically attract relative to competing outlets. Rather than requiring observed revenue data, it infers competitive positions from observable store attributes and demographic configurations. The framework is designed for integration within retail IS, providing a spatially grounded foundation for data-driven pricing and assortment decisions at the local market level.

Keywords: Store Potential Estimation, Spatial Interaction Modelling, Local Markets, Retail Information Systems.

1 Introduction

Retail organizations increasingly rely on information systems (IS) to support marketing mix decisions across pricing, assortment management, and procurement and replenishment activities [4, 9, 26, 30]. These systems translate large volumes of market data into operational recommendations that support managerial decision-making, enabling managers to respond to shifting demand conditions, competitive pressures, and consumer heterogeneity at the local level [22]. The quality of such decisions, however, is fundamentally constrained by the quality of market representations that feed into these systems. In environments characterized by dense competitive landscapes and spatially differentiated consumer demand, the ability to reliably estimate local market potential has therefore become a critical analytical capability within retail information systems, as these systems increasingly serve as the primary interface through which managers interpret and act upon market information [30].

Based on the estimation of local market potential, which is characterized by the volume and spending capacity of prospective customers, retailers are better positioned to forecast sales and demands. Accurate sales and demand forecasting sits at the core of several interdependent retail IS functions [19, 20]. These functions span demand-driven procurement and replenishment planning as well as promotional and pricing optimization. By estimating the potential customer volume for a store, retailers can optimize inventory replenishment cycles and negotiate supply contracts with greater leverage, directly strengthening supply chain efficiency [20, 28].

IS incorporating these analyses typically operationalize market potential through spatially defined regions (catchment areas) within which a store can reasonably expect to attract customers. These catchment areas are evaluated either by the total volume of potential customers residing within them or by the aggregate spending capacity they represent. Simple catchment approaches, however, treat potential as a static demographic quantity, distributing it uniformly across all stores within a radius without accounting for competitive dynamics or consumer choice behaviour. Geographic information systems (GIS) address this limitation by integrating gravitational and spatial interaction models, most notably the Huff model [16], which estimate store-level attraction probabilities as a function of store attractiveness and distance. This allows market potential to be allocated across competing stores in proportion to their relative drawing power, producing a behaviourally grounded and competitively sensitive estimate of how much demand a given store can realistically capture within its local market [11]. While spatial interaction models such as the Huff model provide a well-established framework for modelling consumer choice across competing stores, their empirical application typically relies on observed store-level sales or market share data for calibration and validation. In many real-world retail environments, however, such data are unavailable for competing stores, creating a methodological challenge for estimating local competitive positions and store-level market potential. Consequently, while spatial interaction models offer a theoretically sound representation of consumer choice, their application in competitive retail environments is often constrained by the lack of observable store-level sales data for competing retailers.

The practical relevance of store-level potential estimates becomes particularly clear in the context of pricing and assortment decisions [7, 13]. In brick-and-mortar retail, prices are rarely set in isolation from the competitive environment: the interplay between retailers in a shared local market can be interpreted as a strategic interaction among retailers. This means competitive position, informed by the relative potential of each store, determines whether active or passive pricing policies are appropriate [2, 25]. Retailers commanding a dominant position within their local catchment area have greater latitude to set prices independently, while those operating under competitive pressure must respond to market leaders. Similarly, assortment planning depends on an understanding of which competitors operate within reach of the same customer base and to what extent their assortments overlap. Store potential estimates, by characterizing the spatial distribution of demand and the competitive intensity of the local market, provide the informational foundation for both of these decisions.

For stationary retail, these competitive dynamics unfold within geographically bounded local markets. These are defined here as the spatial area within which a limited set of stores realistically compete for the same pool of customers, delimited either by a fixed radius or by administrative boundaries such as ZIP codes. Estimating store potential within such markets is not straightforward. While retailers are legally required to disclose revenue figures, these are reported at the aggregate organizational level and cannot be decomposed to individual stores or local markets without introducing substantial bias. Direct observation of store-level demand is therefore rarely feasible, and store potential must be estimated from observable inputs (e.g., store attributes, geographic configurations, and demographic data) through spatial modelling. This is precisely the gap that gravitational models such as the Huff model are designed to address.

Against this backdrop, this paper proposes a conceptual framework for estimating store-level market potential in geographically bounded local markets under limited availability of sales data. Building on a localized adaptation of the Huff model, the framework integrates store attractiveness, consumer travel behaviour, and spatial demand distributions to approximate the potential customer volume a store may attract relative to competing outlets. Rather than relying on directly observable store-level revenue data the approach uses spatial modelling to infer competitive positions from observable market characteristics such as store attributes, geographic configurations, and demographic demand structures.

The contribution of this study is therefore not the bounding of choice sets by distance, which is well established in spatial economics, but the design of an IS artifact that estimates store-level competitive position *under the absence of competitor sales data* by inferring it from observable store attributes and demographic structure, and that exposes this estimate in a form directly consumable by the pricing, replenishment, and assortment functions of a retail information system. The framework's novelty thus lies in the conjunction of data-constrained competitive inference and downstream IS integration, rather than in any single component of the underlying spatial model. As this study represents a research-in-progress effort, the proposed model is intended as a conceptual and analytical basis for future empirical evaluation. Subsequent research will assess the validity of the spatial approximations using observed customer flow data and store-level traffic patterns.

2 Retail Information Systems as Decision Support Infrastructure

The integration of analytical models into organizational decision-making has been a central concern of IS research since the emergence of Decision Support Systems (DSS) as a field. Early conceptualizations positioned DSS as computer-based systems designed to support rather than replace managerial judgment in semi-structured decision environments, precisely the conditions under which retail pricing and assortment decisions are made [27]. Subsequent work extended this framing to settings where decisions are spatially structured and data-intensive, recognizing that the value of a DSS depends not only on the underlying model but on its embeddedness within the information infrastructure of the organization [5].

Retail IS represent a specific instantiation of this broader DSS tradition. Their function is to translate heterogeneous operational data e.g., sales records, inventory states, competitor activity, and demographic demand signals, into structured recommendations that support marketing mix decisions across pricing, assortment, and replenishment [4, 9]. As Weber and Schütte [30] document, the adoption of AI-driven analytical capabilities within these systems has accelerated markedly, yet remains concentrated in functions where training data are abundant and outcomes directly observable. Demand forecasting and price optimization, for instance, have benefited substantially from machine learning approaches precisely because historical transaction data provide a dense feedback signal [19, 20]. By contrast, functions that depend on competitor-level market information, and are therefore data-constrained by design, have received comparatively less systematic IS support, despite their strategic importance.

This gap is particularly pronounced in the estimation of local market potential, which requires reasoning about the spatial distribution of demand relative to competing outlets. Existing retail IS tend to operationalize market context through static demographic proxies (e.g., catchment population counts, area income levels) that are readily available but theoretically impoverished: they treat potential as a property of geography rather than of competitive interaction [11, 18]. The result is that decisions sensitive to local competitive structure, above all, pricing and assortment positioning, are made with representations of the market that abstract away the very dynamics they are intended to respond to.

Spatial interaction models address this limitation by grounding market potential estimates in a behavioural theory of consumer choice. Within a GIS environment, they can be operationalized as components of a spatially aware DSS: the model ingests heterogeneous data layers (store attributes, road network geometries, demographic grids), produces probabilistic estimates of competitive demand capture, and passes these estimates downstream to pricing and assortment modules. In this configuration, the GIS is not merely a visualization platform but an integration and computation layer within the IS, hence transforming spatial data into decision-relevant market representations. This positions store potential estimation as an IS artifact problem: the design challenge lies not in the spatial model itself, which is well-established, but in specifying a formulation that is tractable within the data constraints typical of real retail IS environments and connectable to the downstream decision functions it is meant to inform.

The framework proposed in this paper responds to this challenge. By adapting the Huff model to a localized, data-constrained setting and embedding it within GIS-integrated retail IS infrastructure, the paper contributes a conceptual design artifact, in the sense of Hevner et al. [12], that extends the analytical reach of retail decision support into competitive market contexts where existing system capabilities fall short.

3 Store Potential and Catchment Areas

Estimating the demand a store can realistically attract within its local market requires models that account for both the spatial distribution of consumers and the competitive dynamics among stores. Spatial interaction models address this by treating consumer patronage as a probabilistic function of store attractiveness and distance, allowing potential demand to be distributed across competing stores in a behaviourally grounded way [15, 29]. The practical deployment of such models, however, depends on information systems infrastructure capable of integrating the heterogeneous spatial datasets they require. This includes demographic demand distributions, store attributes, road network configurations, and competitor locations. GIS have emerged as the primary technological environment for this purpose, enabling the combination of spatial data layers within a unified analytical platform and making store potential estimation an operational IS capability rather than a purely theoretical exercise [18].

The most influential of these models is the probabilistic attraction model proposed by Huff [16]. While originally developed to estimate consumer attraction to shopping centres, the model generalizes naturally to individual stores and provides a theoretically sound basis for estimating store-level potential within a geographically bounded competitive environment. The original model is given by

$$P_{ij} = \frac{\frac{S_j}{{T_{ij}}^{\lambda}}}{\sum_{j=1}^{n} \frac{S_j}{{T_{ij}}^{\lambda}}}, \tag{1}$$

where P_{ij} determines the probability of a customer traveling from region i to store j, S_j denotes the area of the store, T_{ij} represents the travel time from region i to store j, and λ represents an empirical parameter for distance decay. Subsequent applications extended the model by introducing an attractiveness elasticity parameter α, replacing S_j with A_j^{α} to reflect the diminishing marginal attractiveness of larger stores. Thereby a double-sized store does not necessarily draw double the customers. Further adaptations replaced travel time T_{ij} with straight-line distance D_{ij}, simplifying application in contexts where travel time data are unavailable [6, 8, 10]. Within GIS environments, these inputs are typically derived from integrated data layers e.g., store footprint data, census demographic grids, and road network geometries, allowing the model to be parameterized and executed directly within the spatial analytics infrastructure of the IS.

The spatial foundations underlying the Huff model were established earlier by Hotelling [14], whose linear model demonstrated the fundamental importance of a retailer's distance to potential customers and competitive distance to rival stores. Hotelling's contribution lies in formalizing the spatial dimension of retail competition. His insight shows that store location relative to both consumers and competitors shapes demand, though his deterministic and highly abstract framework is difficult to operationalize in real local markets without strong structural assumptions.

An extension of Hotelling's spatial logic was introduced by Salop [21], who replaced the linear market with a circular one, allowing for a more realistic representation of competition among multiple retailers. Salop's model reinforces the empirical relevance of local markets as spatially bounded competitive units, showing that a limited set of stores compete for the same pool of customers within a defined geographic area. Like Hotelling, however, Salop's model is deterministic and assumes an even distribution of customers across space, limiting its applicability to the heterogeneous demand distributions encountered in real retail settings.

A more recent contribution by Saleh (2007) proposes a generic framework for estimating store attraction across segmented markets, combining an information entropy concept with an attraction model that accounts for customer heterogeneity and product attributes such as quality. This approach is theoretically richer than the Huff model and captures behavioural heterogeneity that simpler models abstract away. However, the additional parameters it requires must be estimated or assumed prior to application, making it difficult to deploy in data-constrained environments where competitor-level information is limited and harder to integrate into GIS-based retail IS where input data availability is a binding constraint.

Contemporary GIS platforms such as ESRI ArcGIS and cloud-based spatial analytics environments have made Huff-type store potential models increasingly accessible as operational IS components [23]. These platforms support the assembly of multi-source spatial datasets into integrated analytical pipelines. This can be achieved by combining point-of-interest databases, administrative demographic layers, and user-generated data such as store visit frequencies from mapping services. Crucially, GIS environments do not merely visualize spatial outputs but serve as data integration and decision support infrastructures: potential estimates generated within them can be connected to downstream IS functions such as pricing engines, assortment planning tools, and replenishment systems. This integration transforms store potential from a static analytical output into a dynamic input for operational retail decision-making. Despite these advances, however, the systematic embedding of spatial interaction models within retail IS remains underdeveloped in both academic research and industry practice, with potential estimates rarely connected to the marketing mix decisions they are most relevant to.

Taken together, these models and their GIS implementations establish that store potential is best understood as a spatially structured outcome of competitive interaction rather than a static demographic quantity. Among the available approaches, the Huff model offers the most tractable foundation for operationalizing this insight under real-world data constraints: it requires only store size and geographic distance as inputs, produces probabilistic estimates that reflect competitive dynamics, and has been extensively validated across retail and geographic contexts. Its compatibility with GIS data infrastructures further makes it a natural candidate for integration into retail IS. These properties make it a suitable basis for a store potential estimation framework applicable to local markets where competitor sales data are unavailable, and for embedding that framework within the IS environments through which retail decisions are operationally supported.

4 The market share estimation algorithm

We propose a localized adaptation of the classical Huff model that explicitly estimates the demand a focal store can realistically attract within its competitive local market. Rather than treating market potential as a static demographic quantity, the framework distributes available demand across competing stores as a function of their relative attractiveness and spatial accessibility. The model consists of three components: a localized choice set definition, a store potential estimator, and a competitive demand ratio that contextualizes the estimated potential within the local market structure.

We first restrict the set of stores that customers from a given region i consider when making patronage decisions. Consistent with the literature on spatial shopping behaviour, we assume that customers will not travel beyond a fixed maximum distance R, reflecting empirically observed limits on consumer travel willingness in retail contexts. The attraction probability for a customer from region i toward store j is therefore given by

$$H_{ij} = \frac{\frac{S_j}{{D_{ij}}^{\lambda}}}{\sum_{k\epsilon\Gamma_i}^{n} \frac{S_j}{{D_{ij}}^{\lambda}}}, \tag{2}$$

where the choice set is defined as

$$\Gamma_i = \{j : D_{ij} \leq R_i\}. \tag{3}$$

Here, S_j denotes the attractiveness of store j, operationalized as store size or selling space. D_{ij} represents the straight-line distance from region i to store j, and λ is an empirical distance decay parameter. Γ_i denotes the set of stores reachable from region i within the region dependent radius R_i. Depending on a rural or urban setting, the radius is set to be larger or smaller. Stores beyond this radius contribute an attraction probability of zero, yielding a spatially bounded model that reflects geographically realistic patronage patterns. Within a GIS environment, both the distance matrix D_{ij} and the reachable store set Γ_i can be derived directly from integrated spatial data layers, making the choice set operationally tractable without requiring observed competitor sales data.

Given the attraction probabilities derived in component one, we estimate the total potential customer volume a store j can expect to attract across all regions i within its catchment area. This quantity, namely the store's market potential, represents the expected demand units drawn to the store given its competitive environment and is given by

$$P_j = \sum_i C_{ij}, \tag{4}$$

where the contribution of region i to store j is

$$C_{ij} = \omega_i \times H_{ij}. \tag{5}$$

Here ω_i denotes the total number of demand units in region i, such as population counts, household numbers, or estimated shopping trip frequencies, which are typically sourced from census demographic layers integrated within the GIS environment. To contextualize this estimate, we additionally compute the total available demand within the store's effective catchment area, independent of competition:

$$W_j = \sum_{i:\, D_{ij} \leq R} \omega_i \tag{6}$$

This quantity captures how many potential customers reside within reach of the store, providing a demand ceiling against which the competitively allocated potential can be assessed. Finally, to situate the store's estimated potential within its local competitive environment, we define a competitive demand ratio as the proportion of available catchment demand that the store can expect to attract given the presence of competing outlets:

$$S_j = \frac{P_j}{W_j} = \frac{\sum_i \omega_i H_{ij}}{\sum_{i:\, D_{ij} \leq R_i} \omega_i} \tag{7}$$

This ratio reflects the store's competitive position within its local market, accounting simultaneously for consumer travel behaviour, store attractiveness, and the spatial distribution of demand. A ratio approaching one indicates a dominant store with limited effective competition within its catchment, while lower values signal competitive pressure from nearby alternatives. This measure provides the direct informational input for pricing and assortment positioning decisions: a store with a high competitive demand ratio operates in conditions more conducive to active pricing, while stores with lower ratios are more likely to operate as price followers within their local market.

5 Discussion

The proposed model inherits several assumptions from the classical Huff model that warrant critical discussion. As with most economic models that depict customer behaviour, the Huff model assumes rational and profit-maximising behaviour of the customers, which is very simplified. However, this abstracted model is well established in empirical research and is consistent with spatial interaction theory, since it applies probabilistic spatial interaction based on gravitation and utility [1]. While the distance and attractiveness decay parameter α and β transparently model the effect of attractivity and distance, in our model these parameters are static. They do not capture reality beyond homogeneous customer behaviour and miss different product-group-specific or region-specific sensitivity and elasticity. The distance in our model is further modelled as straight-line distance, which abstracts from reality, where customers need to drive or walk towards regions of interest like stores or shopping centres. Still, the Huff model is one of the most established ones in spatial competition [3], location and expansion research [17] and geography and transportation studies [24].

The choice of radius is a significant restriction compared to the original model. While it is a realistic operationalisation, reflecting a customer catchment area, it must be carefully chosen. Dependent on the chosen radius, there can be border-effects, which cut off large markets just outside the radius, who would have had a significant influence on the model. This limitation of the radius aligns with empirical research on customers driving distance and time [8, 10, 28]. However, the radius should be dependent on the type of the location of the retail store, since the travel distance customers are likely to travel does vary depending on urban or rural settings.

Further, the attractivity of a store that attracts customers is represented by a proxy in the Huff model in form of the sales area of a store. This generally functions well, since sales area correlates with store-level demand potential. But, attraction to a store does not solely rely on the sales area, since customers are always interested in the retailers image, services, and quality [29]. While traditional retailer may have a large sales area, the quotient of sales per sales area highly varies for discounter, thus including some bias into the proxy. Store size can nonetheless be supplemented or replaced by customer visit frequencies and dwell time data retrievable through mapping service APIs. These data sources are increasingly accessible within GIS-integrated retail IS environments and provide a behaviourally grounded proxy for store attractiveness.

The model itself is a purely mathematical representation of an estimation engine layer that can be integrated into pricing IS. It serves as an intermediator between the GIS-integrated layer and the core retail IS functions covering pricing engine, replenishment and demand forecasting or assortment planning. With the resulting potential estimation directly integrated into an automatic pipeline, retailers can more accurately determine prices based on the aforementioned factors.

6 Conclusion and further Evaluation

The aim of this research-in-progress paper was to propose and discuss a conceptual framework for estimating store-level market potential within geographically bounded local markets under limited availability of competitor sales data. We chose the well-established Huff model as our basis, since it allows the observation of multiple stores and can be applied to multiple markets and includes probabilistic customer attraction. Our presented extension of the Huff model included a limiting radius to make the model robust and efficient for real world application, while addressing customers travel distance. Based on this extension, we showed how to estimate the store potentials for each competitor within the local market.

For our future research especially the evaluation of the proposed model, we plan the following: First, we analyse customer data and scanner data from a large German retailer, to prove our assumption of limiting the radius in our proposed model. Then implement and integrate our model into the retailer's IS and analyse a region the retailer operates stores within. Thereby we can calculate each stores potential relative to the retailers' competitors. Since having access to customer data, we then plan to evaluate our model with real attraction data, analysing customer flows.

As a second part, we plan to integrate a temporal dimension into our model to correctly capture time dynamics in local markets. Currently our model assumes every potential customer from a region to visit one store at a time. While this applies to all time frames, this abstracts from reality, where customers switch brands and loyalty. Thus, we plan on adding a changing probability and likelihood for visiting a retailer's store, capturing time dynamics. Further, we plan to extend our model to allow customers to visit multiple stores in a time horizon, capturing reality's customer behaviour, where customers may visit a bakery in the morning and go grocery shopping in the evening. By extending our model, retailers cannot only estimate their market potential but also apply a forecast on how their sales and revenue will be. This enables retailers to perform strategic price management and ultimately strengthening the retailer's competitive position in local and global markets.

References

1. Batten DF, Boyce DE (1987) Chapter 9 Spatial interaction, transportation, and interregional commodity flow models. In: Handbook of Regional and Urban Economics. Elsevier, pp 357–406
2. Besbes O, Sauré D (2016) Product Assortment and Price Competition under Multinomial Logit Demand. Production and Operations Management 25:114–127. doi: 10.1111/poms.12402
3. Beule M de, van den Poel D, van de Weghe N (2014) An extended Huff-model for robustly benchmarking and predicting retail network performance. Applied Geography 46:80–89. doi: 10.1016/j.apgeog.2013.09.026
4. Brackmann C, Hütsch M, Wulfert T (2023) Identifying Application Areas for Machine Learning in the Retail Sector: A Literature Review and Interview Study. SN COMPUT SCI 4:426. doi: 10.1007/s42979-023-01888-w
5. DeLone WH, McLean ER (2003) The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. Journal of Management Information Systems 19:9–30. doi: 10.1080/07421222.2003.11045748
6. Drezner T, Drezner Z, Zerom D (2022) An extension of the gravity model. Journal of the Operational Research Society 73:2732–2740. doi: 10.1080/01605682.2021.2015256
7. Dukes AJ, Geylani T, Srinivasan K (2009) Strategic Assortment Reduction by a Dominant Retailer. Marketing Science 28:309–319. doi: 10.1287/mksc.1080.0399
9. Giat Y, Bouhnik D (2021) A Decision Support System and Warehouse Operations Design for Pricing Products and Minimizing Product Returns in a Food Plant. IJIKM 16:39–54. doi: 10.28945/4692
10. Grewal D, Kopalle P, Marmorstein H et al. (2012) Does Travel Time to Stores Matter? The Role of Merchandise Availability. Journal of Retailing 88:437–444. doi: 10.1016/j.jretai.2012.03.002
11. Hernández T, Bennison D (2000) The art and science of retail location decisions. International Journal of Retail & Distribution Management 28:357–367. doi: 10.1108/09590550010337391
12. Hevner AR, March ST, Park J et al. (2004) Design Science in Information Systems Research1. MIS Quarterly 28:75–106. doi: 10.2307/25148625
13. Hinterhuber A (2024) What every manager should know about pricing. JBS 45:253–266. doi: 10.1108/JBS-11-2022-0192
14. Hotelling H (1929) Stability in Competition. The Economic Journal 39:41. doi: 10.2307/2224214

15. Huber J, Puto C (1983) Market Boundaries and Product Choice: Illustrating Attraction and Substitution Effects. J Consum Res 10:31. doi: 10.1086/208943
16. Huff DL (1964) Defining and Estimating a Trading Area. Journal of Marketing 28:34–38. doi: 10.1177/002224296402800307
17. Kress D, Pesch E (2012) Sequential competitive location on networks. European Journal of Operational Research 217:483–499. doi: 10.1016/j.ejor.2011.06.036
18. Longley PA, Goodchild MF, Maguire DJ et al. (2015) Geographic information science & systems, 4. ed. Wiley, Hoboken, NJ
19. Pallathadka H, Ramirez-Asis EH, Loli-Poma TP et al. (2023) Applications of artificial intelligence in business management, e-commerce and finance. Materials Today: Proceedings 80:2610–2613. doi: 10.1016/j.matpr.2021.06.419
20. Pereira MM, Frazzon EM (2021) A data-driven approach to adaptive synchronization of demand and supply in omni-channel retail supply chains. International Journal of Information Management 57:102165. doi: 10.1016/j.ijinfomgt.2020.102165
21. Salop SC (1979) Monopolistic Competition with Outside Goods. The Bell Journal of Economics 10:141. doi: 10.2307/3003323
22. Schulte S, Parra-Moyano J, Schmedders K (2022) In NVivo Veritas: How Information Systems Increase the Flexibility and Relevance of Strategic Management Accounting. In: ICIS 2022 Proceedings, vol 10
23. Scott LM, Janikas MV (2009) Spatial Statistics in ArcGIS. In: Fischer MM (ed) Handbook of Applied Spatial Analysis. Springer, Dordrecht, pp 27–41
24. Shi M, Janowicz K, Cai L et al. (2021) A Socially Aware Huff Model for Destination Choice in Nature-based Tourism. AGILE GIScience Ser 2:1–16. doi: 10.5194/agile-giss-2-14-2021
25. Simon H, Faßnacht M (2019) Price management. Strategy, analysis, decision, implementation. Springer, Cham
26. Soleimani M (2022) Buyers' trust and mistrust in e-commerce platforms: a synthesizing literature review. Inf Syst E-Bus Manage 20:57–78. doi: 10.1007/s10257-021-00545-0
27. Sprague RH (1980) A Framework for the Development of Decision Support Systems. MIS Quarterly 4:1–26. doi: 10.2307/248957
28. Supriharyanti E, Agung DA, Agrippina YR et al. (2022) Proximity and Retail Loyalty: Mediation of Time Convenience. AJBR 12. doi: 10.14707/ajbr.220130
29. Teller C, Reutterer T (2008) The evolving concept of retail attractiveness: What makes retail agglomerations attractive when customers shop at them? Journal of Retailing and Consumer Services 15:127–143. doi: 10.1016/j.jretconser.2007.03.003
30. Weber FD, Schütte R (2019) State-of-the-art and adoption of artificial intelligence in retailing. DPRG 21:264–279. doi: 10.1108/DPRG-09-2018-0050