

From Data-Driven Personalization to Culturally Adaptive Merchandising: A Systematic Review and the CAMI-DM Framework

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**From Data-Driven Personalization to Culturally Adaptive Merchandising: A Systematic
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Abstract

Artificial intelligence (AI), behavioral analytics, recommender systems, and digital retail technologies are increasingly used to personalize consumer experiences. Yet personalization based primarily on observed behavior may remain insensitive to cultural meaning, local practices, language, symbolic preferences, and context. This study revisits the literature on data-driven intelligent multicultural merchandising and develops an integrative research framework rather than a descriptive inventory of technologies. A PRISMA-guided systematic review was conducted using Scopus. A broad search retrieved 129 records; after restricting the corpus to Articles and Reviews, 60 records were screened by title and abstract. Thirty-four records remained after title/abstract screening; 12 were excluded at a preliminary eligibility check, and 22 reports were advanced to retrieval. Three could not be retrieved and 19 were assessed for eligibility; nine were excluded, leaving ten studies in the confirmed synthesis set. The included studies cover big-data and machine-learning analytics, Transformer-based sentiment analysis, chatbot recommendation, automated retail, cross-border AI promotion, phygital retail environments, cultural-product recommendation, and culturally contingent consumer responses. The evidence is fragmented across these streams. Within the screened corpus, no confirmed study operationalized in one end-to-end framework the joint sequence of behavioral data, multidimensional cultural context, intelligent adaptation, merchandising decisions, observed consumer response, and feedback-driven updating. Building on this gap, the paper proposes CAMI-DM (Culturally Adaptive, AI- and Data-driven Merchandising), an architecture linking behavioral signals, cultural and situational context, adaptive intelligence, customer experience, trust, behavioral response, and commercial performance. A quadratic assignment problem (QAP) is proposed as the spatial optimization layer, with distance constraints that preserve metric consistency. The study concludes with a set of testable hypotheses and an empirical protocol for physical, digital, and phygital retail settings.

Keywords: culturally adaptive merchandising; artificial intelligence; behavioral data; retail personalization; cross-cultural consumer behavior; QAP; phygital retail; CAMI-DM

1. Introduction

Retailing is increasingly organized around the continuous collection and interpretation of consumer data. Transaction histories, product interactions, browsing paths, loyalty-program records, mobile interactions, digital reviews, and in-store traces can be transformed into signals for recommendation, segmentation, demand prediction, and experience design. In parallel, artificial intelligence (AI) has expanded the ability of retailers to infer preferences, automate decisions, and personalize interactions at increasingly fine temporal scales (Davenport et al., 2020; Wedel & Kannan, 2016). These developments have also extended merchandising beyond static product placement toward dynamic combinations of assortment, presentation, promotion, recommendation, and spatial configuration.

However, the increasing technical capacity to personalize does not resolve a more fundamental question: personalized according to which context? Consumer behavior is shaped not only by individual history but also by meanings, social norms, values, language, religious and belief-related practices, visual conventions, household routines, seasonal events, and locally embedded preferences.

Cross-cultural research shows that the same interface, recommendation mechanism, or visual presentation can be interpreted differently across cultural contexts (Wang et al., 2023). Recent retail studies similarly show that cultural constructs can alter responses to AI-mediated recommendations, trust, and automated shopping environments (Baingam & Wittayakom, 2026; Landim et al., 2025; Niu et al., 2026).

This issue is especially important for multicultural retail environments, where customers may share a country, city, or store while differing in language practices, values, beliefs, consumption traditions, or symbolic expectations. A national label is therefore an incomplete representation of cultural context. Hofstede's dimensions remain useful for comparative analysis, but they do not by themselves capture intra-cultural heterogeneity, hybrid identities, digitally mediated communities, or context-dependent behavior (Hofstede, 2001; de Mooij, 2019). For a data-driven merchandising system, cultural context should therefore be represented as a multidimensional and updateable construct rather than as a fixed country code.

The literature is developing rapidly, but it remains fragmented. One group of studies focuses on AI-enabled personalization and recommendation. Another examines cultural differences in consumer responses to AI. A third investigates behavioral analytics and data-driven retail. A fourth addresses physical or phygital retail environments, visual presentation, or spatial experience. Recent empirical studies provide strong evidence for individual pieces of the problem. Putri et al. (2025), for example, use big-data analytics and machine learning to identify drivers of demand in modest fashion e-commerce. Liu and Pareti (2026) analyze 33,464 online wine reviews from China and Italy with Transformer-based natural language processing and cultural dimensions. Landim et al. (2025) compare a chatbot recommender across Brazilian and English consumers. Wang et al. (2023) demonstrate culturally contingent effects of product-image background. Yet these contributions do not establish a unified, feedback-driven merchandising architecture.

The original version of this study was framed primarily as a bibliographic description of intelligent multicultural merchandising. The present paper deliberately changes that positioning. Instead of using approximate literature-volume ranges or simply listing technologies, it uses a reproducible Scopus search, an explicit PRISMA-guided selection process, a structured synthesis of the studies that passed relevance screening, and a theory-building framework intended to explain how the different streams can be integrated. The contribution is therefore not the claim that AI, personalization, culture, or merchandising are individually new. The contribution is the integration of these streams into a single research architecture and an empirical agenda for testing that architecture.

The study addresses six research questions: RQ1, how has the research landscape at the intersection of AI, data-driven retail, and cultural context evolved within the retrieved corpus? RQ2, which types of technologies, data, retail settings, and consumer outcomes are represented? RQ3, how is culture operationalized in data-driven retail and AI studies? RQ4, how do the included studies connect behavioral data, AI-enabled personalization, cultural adaptation, and merchandising? RQ5, what methodological and conceptual gaps remain? RQ6, how can these gaps be translated into an integrative, testable framework for culturally adaptive merchandising?

2. Theoretical Background

2.1. Merchandising as a decision system

Merchandising traditionally concerns the selection, placement, presentation, and promotion of products to facilitate consumer choice while supporting commercial objectives. Research on shelf-space allocation and store layout has long shown that spatial decisions can influence attention, search, convenience, and sales (Drèze et al., 1994; Hübner et al., 2013). More recent retailing research treats the store as part of a broader experience system in which physical and digital touchpoints interact. The implication for this paper is that merchandising should be treated not only as a static arrangement but as a sequence of decisions that can be updated when new information becomes available.

2.2. Behavioral data and customer journeys

Behavioral data capture what consumers do rather than only what they declare that they prefer. In digital retail, such data may include clicks, search queries, product views, dwell time, recommendation responses, cart additions, purchases, and reviews. In physical stores, tracking technologies can add movement paths, dwell time, aisle visits, product interactions, queue behavior, and location-based exposure. The customer-journey literature emphasizes that experience is distributed across multiple touchpoints and stages (Lemon & Verhoef, 2016; Becker & Jaakkola, 2020). A CAMI-DM system consequently needs a temporal representation of behavior rather than a one-time customer profile.

2.3. AI-enabled personalization

AI-enabled personalization uses machine learning, recommender systems, natural-language processing, computer vision, predictive analytics, or generative systems to infer preferences and select relevant interventions. Davenport et al. (2020) argue that AI changes marketing by increasing prediction and automation capacity, while subsequent retail studies show how recommendation systems can be embedded into customer interfaces. The important distinction for CAMI-DM is between technological personalization and contextual adaptation. The former asks which option is likely to fit an individual based on observed signals; the latter asks whether that option, presentation, message, or placement remains culturally appropriate in the situation in which the consumer encounters it.

2.4. Culture as a multidimensional consumer context

Culture influences interpretation, expectations, information processing, social meaning, and consumption practices. Hofstede's framework provides a comparative language for dimensions such as individualism-collectivism and uncertainty avoidance, while de Mooij emphasizes the relationship between culture and consumer behavior. Yet a data-driven merchandising model should avoid collapsing culture into nationality. Recent research illustrates the diversity of operationalizations: individualism in AI-chatbot research, Buddhist reflective cognition in Thailand, mianzi in Chinese business settings, and holistic versus analytic thinking in cross-border e-commerce (Baingam & Wittayakom, 2026; Niu et al., 2026; Wang et al., 2023). These studies suggest a broader formulation in which cultural context is represented by a vector of relevant, ethically collected attributes and not by a single country variable.

2.5. Experience, trust, and consumer response

AI-mediated decisions can influence perceptions of relevance, convenience, agency, and trust. The consumer response may therefore occur through multiple mechanisms rather than through purchase

alone. The service and customer-experience literature emphasizes perceived value, emotional response, cognitive processing, and subsequent behavioral response (Lemon & Verhoef, 2016; Becker & Jaakkola, 2020). CAMI-DM consequently positions customer experience and trust between adaptive merchandising decisions and behavioral outcomes. This structure also creates space for privacy, transparency, and consumer autonomy as design constraints rather than after-the-fact ethical additions.

3. Research Questions and Contribution

RQ1. What are the main technological, data, cultural, and retail characteristics of research at the intersection of AI-enabled retail and cultural adaptation in the retrieved Scopus corpus?

RQ2. Which consumer outcomes and adaptation mechanisms are currently studied?

RQ3. How is cultural context represented across the included studies?

RQ4. To what extent are behavioral data, AI, culture, and merchandising integrated rather than studied separately?

RQ5. Which conceptual, methodological, and operational gaps limit the development of end-to-end culturally adaptive merchandising?

RQ6. What integrative framework and empirical propositions can connect the identified evidence streams?

3.1. Contributions

The paper makes four contributions. First, it replaces non-reproducible estimates of literature volume with an explicit and auditable Scopus search and screening process. Second, it separates technological personalization from cultural adaptation, showing that the two are complementary rather than synonymous. Third, it synthesizes evidence from data-driven retail, culturally contingent consumer response, visual merchandising, and phygital experience into a single CAMI-DM architecture. Fourth, it translates the conceptual gap into a testable empirical design and a spatial optimization module based on the quadratic assignment problem (QAP).

4. Methodology

4.1. Review design

The review follows a PRISMA 2020-guided reporting structure. PRISMA 2020 provides a checklist and flow-diagram templates for reporting why a review was conducted, how evidence was identified and selected, and what was ultimately included (Page et al., 2021). The present review is a systematic evidence synthesis with theory-building objectives; it is not presented as a meta-analysis because the included studies are heterogeneous in design, data, constructs, and outcomes.

4.2. Search strategy

Scopus was used as the sole bibliographic database for study identification. This choice was made to provide a structured, reproducible, and sufficiently broad documentary corpus covering the scientific literature relevant to the research question. The main search was conducted on September 22, 2026.

An expanded search query was developed around three mandatory conceptual blocks: smart technologies and data, retail or merchandising, and culture or cultural adaptation. A narrower sensitivity search additionally required the explicit presence of terms related to consumer behavior and personalization and returned 32 records. These records were included within the 129 records retrieved

by the expanded search. Therefore, the latter was retained for the screening process in order to reduce the risk of excluding potentially relevant studies.

The broad Scopus query was:

TITLE-ABS-KEY(

("artificial intelligence" OR "machine learning" OR "deep learning" OR "intelligent system*" OR "recommender system*" OR "recommendation system*" OR "predictive analytics" OR "big data" OR "generative AI") AND

(retail* OR merchandising OR "visual merchandising" OR "product placement" OR planogram* OR "store layout" OR "shelf management" OR "smart retail*" OR "digital retail*" OR omnichannel) AND

(culture OR "cultural adaptation" OR "cultural preference*" OR multicultural OR "cross-cultural" OR "cross cultural" OR "cultural context" OR "cultural diversity" OR "local preference*")

)

AND PUBYEAR > 2018

AND PUBYEAR < 2027

AND LANGUAGE(english)

4.3. Search refinement and eligibility

The broad query returned 129 records. The corpus was then limited to Articles and Reviews, yielding 60 records: 54 Articles and 6 Reviews. The title/abstract screening excluded 26 clearly irrelevant records. Thirty-four records remained for preliminary eligibility. At that stage, 12 were excluded for an explicit mismatch with the prespecified scope, leaving 22 reports for retrieval and detailed eligibility assessment. Three could not be retrieved. Nineteen reports were assessed and nine were excluded for lack of a substantive connection to the intersection of AI/data, retail/merchandising, and cultural context. Ten studies remained in the confirmed synthesis set. The selection flow is summarized in Figure 1.

4.3.1 Screening procedure

Screening was conducted using a prespecified eligibility grid derived from the research questions and inclusion/exclusion criteria. Titles and abstracts were first examined to remove records that were clearly outside the scope. The remaining records were subjected to a preliminary eligibility assessment, followed by full-text retrieval where available. Eligibility decisions were recorded in a structured screening table. Ambiguous records were re-examined against the predefined criteria before the final inclusion decision.

Because the review was conducted as a doctoral theory-building study, the screening process was designed to maximize traceability of decisions rather than to claim inter-rater reliability that was not formally calculated.

4.3.2 Methodological quality and relevance appraisal

Because the included studies differed substantially in design, data sources, analytical methods, and research objectives, a single risk-of-bias instrument was not applied uniformly to all studies. Instead, a structured domain-based appraisal was conducted to assess methodological transparency and relevance to CAMI-DM.

Each study was examined across six domains: (1) clarity of research objective, (2) transparency of data and sample description, (3) appropriateness of the analytical method, (4) explicitness of the cultural construct, (5) clarity of the link to retail or consumer decision making, and (6) transparency of study limitations. Each domain was coded as fully reported, partially reported, or insufficiently reported.

This appraisal was used primarily to qualify the strength and transferability of the evidence rather than to exclude studies solely on the basis of methodological score.

Table 1: Summary of Included Studies

Study	Objective	Data/sample	Method	Culture	Retail link	Limitations	Overall relevance
Putri et al. (2025)	✓	✓	✓	✓	✓	✓	Direct
Liu & Pareti (2026)	✓	✓	✓	✓	✓	✓	Direct
Landim et al. (2025)	✓	✓	✓	✓	✓	✓	Direct
Baingam & Wittayakom (2026)	✓	✓	✓	✓	✓	✓	Complementary
Niu, Yu & Dong (2023)	✓	✓	✓	✓	✓	✓	Direct
Ratnayake et al. (2026)	✓	✓	✓	✓	✓	✓	Direct
Sun (2025)	✓	✓	✓	✓	✓	✓	Direct
Niu et al. (2026)	✓	✓	✓	✓	✓	✓	Complementary
Akhtar et al. (2022)	✓	✓	✓	✓	✓	✓	Direct
Wang et al. (2023)	✓	✓	✓	✓	✓	✓	Direct

Direct – contribution to merchandising in the strict sense / Complementary – contributes to merchandising in a complementary way

4.4. Inclusion and exclusion criteria

Table 2: Inclusion and Exclusion Criteria

Criterion	Include	Exclude
Population/context	Retail consumers, retail organizations, digital or physical retail environments, cross-border commerce, fashion retail, cultural-product retail.	Non-retail contexts unless they directly inform a transferable retail mechanism.
Technology/data	AI, machine learning, NLP, recommender systems, behavioral analytics, big data, IoT/AR/VR or related intelligent technologies used substantively.	AI/data mentioned only incidentally or used solely for bibliometric clustering.
Culture	Explicit cultural, cross-cultural, locally embedded, religious/belief-related, symbolic, or culturally contextual construct.	Culture used only as a generic word or only as organizational culture.
Outcome/decision	Consumer behavior, customer experience, recommendation, merchandising, purchase, engagement, trust, satisfaction, or retail decision outcomes	Studies with no meaningful connection to consumer, retail, or merchandising decisions
Publication type	Scopus Article or Review, English, 2019–2026 search window.	Conference-only records, editorials, notes, non-English records, or out-of-window records.

4.5. Data extraction and synthesis

For each retained study, the review extracted year, retail setting, method, technology, data type, cultural construct, consumer or business outcome, adaptation mechanism, and relevance to CAMI-DM. The synthesis was thematic and integrative: findings were grouped into (1) behavioral data and analytics, (2) AI-enabled personalization and recommendation, (3) cultural contingency, (4) physical/phygital merchandising and experience, and (5) feedback and optimization. This approach avoids treating heterogeneous effect estimates as directly commensurable while still identifying structural complementarities across studies.

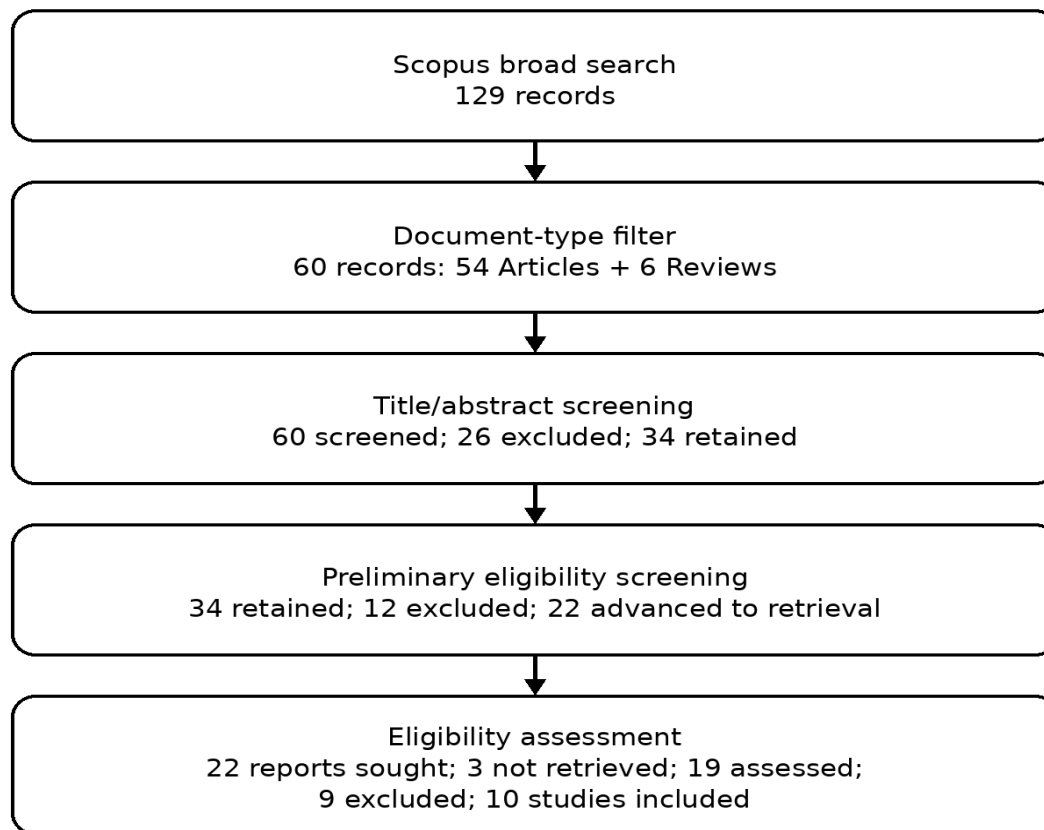


Figure 1. Study selection flow used in the review.

5. Results

5.1. Corpus profile and selection

The final search-and-screening structure produces a compact but information-rich synthesis set. The 60 Article/Review records came from a broader 129-record search. The included studies were published between 2022 and 2026, indicating that the studies satisfying the combined relevance criteria were concentrated in the most recent part of the search window. This concentration should not be interpreted as evidence that earlier work on culture, personalization, or merchandising did not exist; rather, it indicates that earlier work did not survive the joint relevance criteria used here.

Table 3: Study Selection Indicators

Selection indicator	Count
Broad Scopus retrieval	129
Article + Review subset	60
Articles	54
Reviews	6
Title/abstract exclusions	26
Reports advanced to retrieval	22
Preliminary eligibility exclusions	12
Reports not retrieved	3
Reports assessed	19
Eligibility exclusions	9
Confirmed included studies	10

5.2. Characteristics of the included studies

Table 4: Comparative Matrix of Included Studies: Methods, Cultural Contexts, and Implications for the CAMI-DM Framework

Study	Method/data	Retail context	Cultural dimension	CAMI-DM implication
Putri et al. (2025)	Big-data analytics + ML; e-commerce fashion	Modesty-conscious market; price, brand, color, fabric	Culturally/societally specific segment	Data-driven customization of retail strategy
Liu & Pareti (2026)	33,464 online reviews; Transformer/NLP; Hofstede + SDT	China vs Italy; digital wine retail	Hofstede dimensions; motivation/expressio n	Cross-cultural sentiment matrix for retail decision support
Landim et al. (2025)	Chatbot recommender; Brazil/England comparison	Fashion e-commerce	Cross-cultural/contextual differences	Different experience responses to the same recommender
Baingam & Wittayakom (2026)	Survey, n=396; hierarchical regression	Unmanned convenience stores, Thailand	Yonisomanasikara; Buddhist context	Culturally embedded interpretation of trust, risk and acceptance
Niu, Yu & Dong (2023)	Cross-border co-opetition/game-theoretic model	AI livestream and local retail channel	Cultural disparities as cross-border condition	Adaptive promotion/channel logic

Study	Method/data	Retail context	Cultural dimension	CAMI-DM implication
Ratnayake et al. (2026)	Systematic review; 50 publications	Luxury fashion retail interiors; physical/phygital	Digital culture; cultural storytelling	Integration of technology, space and narrative
Sun (2025)	50,000+ visitor sessions; RFID/POS/app logs; Apriori/FP-Growth	Museum cultural-product retail	Cultural-product context	Behavior-aware personalized recommendations
Niu et al. (2026)	Four-study multi-method; aggregate N=6,468	Retail precincts; AI-enabled brand strategy	Mianzi / Chinese cultural prestige	AI sophistication interacts with culturally specific motives
Akhtar et al. (2022)	Digital transformation/business-model analysis	Textile/apparel; supra-omnichannel retail	Socio-cultural shifts in consumer preferences	Real-time data visibility and user-driven innovation
Wang et al. (2023)	Cross-cultural experiments; eye-tracking in Study 3	Cross-border e-commerce; product images	Holistic vs analytic thinking	Culturally contingent visual presentation

5.3. Thematic synthesis

5.3.1. Behavioral data enable adaptation, but culture determines meaning

The strongest data-driven evidence comes from studies that transform consumer traces into actionable representations. Putri et al. (2025) use e-commerce data and machine learning to identify product attributes associated with demand in a culturally specific fashion segment. Liu and Pareti (2026) use 33,464 reviews and Transformer-based sentiment analysis to distinguish evaluation patterns between Chinese and Italian consumers. Sun (2025) shows how more than 50,000 visitor sessions can be transformed into association rules connecting behavior, events, interactions, and cultural-product purchases. These studies support the first pillar of CAMI-DM: behavioral data can provide a dynamic signal about what consumers attend to, choose, value, or revisit.

At the same time, data do not determine meaning by themselves. A color, image, product category, message, or recommendation can carry different meanings in different cultural contexts. Wang et al. (2023) show that contextual image backgrounds can affect consumers differently depending on holistic versus analytic thinking. The implication is that the same behavioral predictor may require different interpretation rules across contexts. CAMI-DM therefore treats behavioral data and cultural context as complementary inputs rather than substitute explanations.

5.3.2. AI personalization is increasingly effective, but not culturally neutral

Landim et al. (2025) provide direct evidence that an AI-enabled chatbot recommendation interface can improve customer experience in fashion e-commerce while producing different magnitudes of response across Brazil and England. Niu et al. (2026) similarly show that advanced AI with real-time analytics and personalized recommendation changes the relationship between a culturally specific motive,

mianzi, and strategic dependence in retail settings. Baingam and Wittayakom (2026) add a culturally embedded interpretation of automated retail acceptance, emphasizing trust, perceived risk, and reflective evaluation. Together, these studies suggest that AI personalization should be treated as a context-dependent intervention rather than as a culturally invariant treatment.

This distinction is central to the CAMI-DM proposal. A conventional recommender estimates relevance from a consumer's history. CAMI-DM adds a contextual layer that asks whether the recommendation, presentation, placement, or interaction is culturally compatible in the current environment. The model therefore separates the ability to predict preference from the ability to adapt the commercial environment responsibly.

5.3.3. Physical, digital and phygital merchandising need a common architecture

The included studies span digital e-commerce, cross-border promotion, automated stores, museum cultural-product retail, luxury retail interiors, and product-image presentation. Ratnayake et al. (2026) show how technology, spatial atmosphere, and cultural storytelling can be integrated in phygital luxury retail. Akhtar et al. (2022) highlight the shift toward digital and supra-omnichannel fashion systems in which consumer preferences and real-time data influence business models. Wang et al. (2023) demonstrate that visual presentation itself can be culturally contingent. These streams imply that merchandising should not be reduced to a planogram: it includes the spatial, visual, informational, and algorithmic elements that shape a shopping environment.

CAMI-DM therefore defines merchandising decisions broadly enough to include assortment, placement, facings, adjacency, signage, color and visual presentation, digital recommendations, promotion, and navigation support. The same adaptation logic can be instantiated physically, digitally, or across phygital touchpoints, while the specific optimization problem may differ by channel.

5.3.4. The feedback loop is the least developed element

Several studies use real-time, behavioral, or transactional data, but the screened corpus does not establish a confirmed end-to-end loop in which a retail system observes the current state, adapts merchandising, measures the resulting consumer response, and then updates the next merchandising decision with an explicit cultural representation. This is the key dynamic gap addressed by CAMI-DM. The model is therefore not a static segmentation framework; it is a state-transition architecture in which the merchandising environment can be updated as evidence accumulates.

5.3.5. Ethics, privacy, and consumer autonomy are constraints on adaptation

Culturally adaptive systems can create value, but they can also intensify profiling and stereotyping. The relevant design question is not simply whether an algorithm can infer cultural attributes, but whether those attributes are necessary, proportionate, explainable, and used to support consumer choice rather than restrict it. The CAMI-DM framework consequently treats privacy, fairness, transparency, and consumer autonomy as constraints on the adaptation engine. Cultural signals should be derived from legitimate sources, validated with stakeholders, and used at the level of relevance needed for the decision rather than as a blanket basis for exclusion.

5.4. Cross-study gap matrix

Table 5: Identified Gaps in the Literature and Responses Provided by the CAMI-DM Framework

Gap	What the corpus provides	What remains missing	CAMI-DM response
Joint integration	Studies provide separate building blocks for AI/data, culture, recommendation, and merchandising.	No confirmed end-to-end framework links all four dimensions in one adaptive decision system.	CAMI-DM integrates the streams at the architecture level.
Dynamic feedback	Real-time analytics and behavior traces are increasingly available.	Explicit state → decision → response → update loops are under-specified for multicultural merchandising.	Introduce temporal feedback and state transition.
Cultural representation	Hofstede, individualism, mianzi, Buddhist reflection, holistic/analytic thinking are used.	Cultural context is often single-construct or country-level.	Use a multidimensional cultural ontology.
Spatial optimization	Studies address visual presentation, space and retail interiors.	Cultural adaptation is not jointly optimized with shelf/slot assignment.	Use QAP with cultural utility and distance constraints.
Physical-digital integration	Studies are rich within individual channels.	A common decision architecture across physical, digital and phygital contexts is missing.	Model merchandising decisions as channel-adaptive outputs.
Business and experience outcomes	Studies report purchase, satisfaction, trust, engagement, or strategic outcomes.	No common chain from cultural relevance to CX/trust/behavior and commercial KPIs.	Link perceptual outcomes to POS/e-commerce and journey metrics.

Research gap

Despite significant advances in AI-enabled retail analytics, data-driven personalization, consumer behavior modeling, and merchandising optimization, the existing literature remains fragmented across technological, behavioral, commercial, and cultural dimensions. In particular, cultural factors are often treated as contextual or geographic attributes rather than as multidimensional variables that can dynamically influence merchandising decisions. Moreover, existing approaches provide limited conceptual integration between behavioral data, cultural context, real-time situational factors, merchandising adaptation, customer response, and feedback mechanisms. This fragmentation reveals a need for an integrated framework capable of dynamically adapting merchandising decisions to heterogeneous cultural and behavioral contexts while incorporating consumer responses into a continuous learning process. To address this gap, this study proposes the Culturally Adaptive, AI- and

Data-driven Merchandising (CAMI-DM) framework, which conceptualizes the sequential and feedback-based relationships between behavioral data, cultural context, Adaptive Cultural Intelligence, context-aware adaptation, merchandising decisions, customer experience, and behavioral response. Scopus was selected as the primary bibliographic database because of its broad multidisciplinary coverage and its relevance to the intersection of artificial intelligence, data analytics, retail, consumer behavior, marketing, and cultural studies. Its advanced search functions and structured bibliographic metadata also facilitate the reproducible identification, screening, and bibliometric analysis of the literature relevant to the CAMI-DM framework

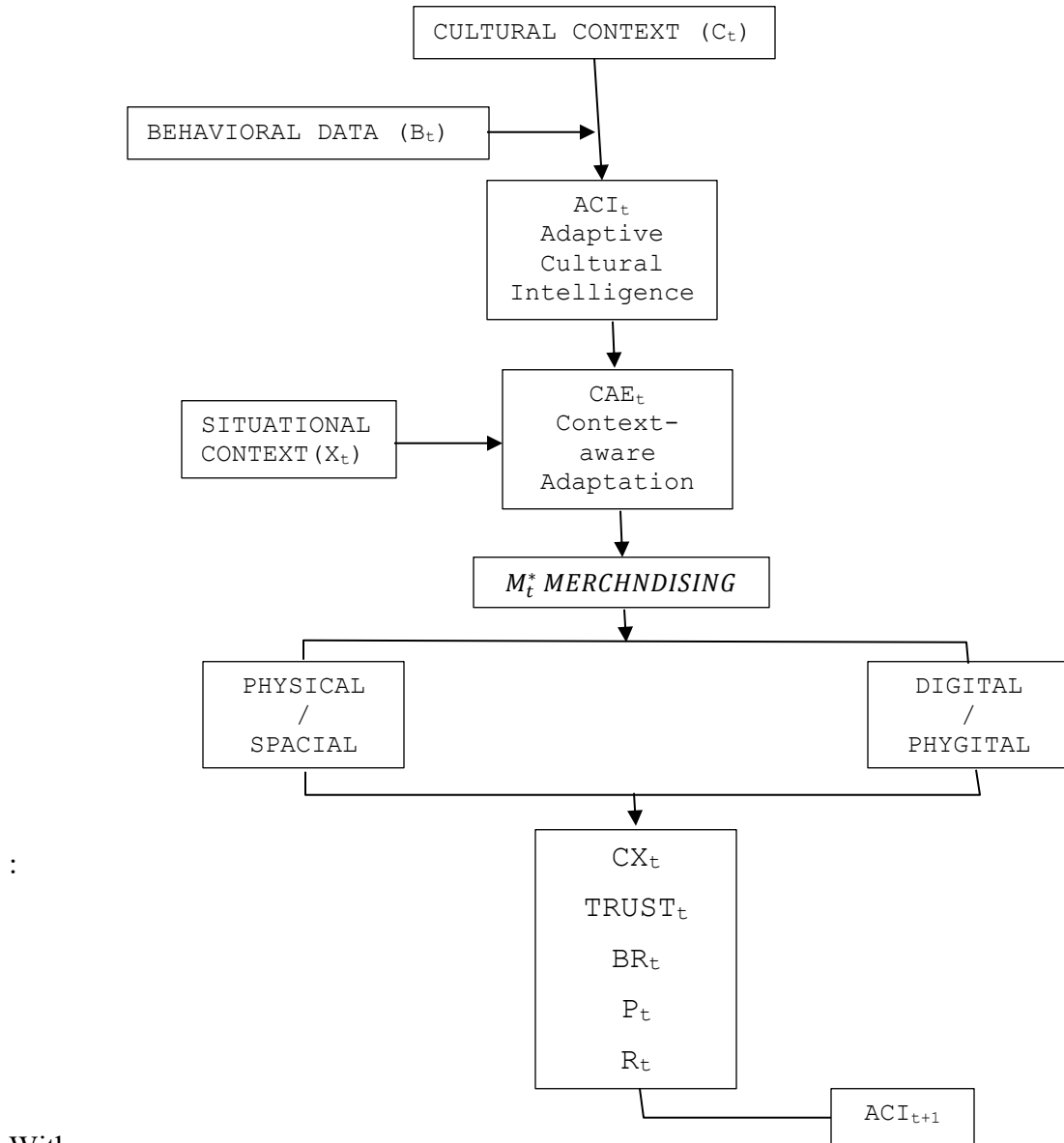
6. The CAMI-DM Framework

CAMI-DM (Culturally Adaptive, AI- and Data-driven Merchandising) is proposed as an integrative architecture for translating consumer signals and contextual knowledge into adaptive merchandising decisions. The framework contains five layers:

1. data and context sensing,
2. adaptive cultural intelligence,
3. context-aware adaptation,
4. merchandising optimization, and
5. consumer/commercial response with feedback.

The architecture is intentionally modular so that a retailer can implement a subset of the components while preserving the conceptual relationships.

Figure 2 : CAMI-DM conceptual architecture



With :

$$S_t = \{B_t, C_t, X_t, R_{t-1}\}$$

$$ACI_t = \sigma(W_B B_t + W_C C_t + W_X X_t + W_R R_{t-1} + b)$$

$$CAE_t = g(ACI_t C_t, S_t, M_t^{candidate}, constraints_t)$$

And

$$M_t^* = \arg \min_x [spatial \ cost - \eta_{cultural/behavioral} \ utility]$$

6.1. State representation

Let the retail state at time t be represented as $S_t = \{B_t, C_t, X_t, R_{t-1}\}$, where B_t denotes behavioral signals, C_t denotes multidimensional cultural context, X_t denotes situational and operational conditions such as stock, price, seasonality, store load, channel, and local events, and R_{t-1} summarizes the observed response from the previous decision cycle. The state representation is dynamic because each merchandising decision can modify the subsequent behavioral and commercial environment. The state transition can therefore be expressed as :

$$S_{t+1} = f(S_t, M_t, R_t, \varepsilon_t)$$

where M_t is the merchandising decision, R_t is the observed response, and ε_t represents unobserved factors and stochastic variation.

This formulation makes CAMI-DM explicitly adaptive : a subsequent merchandising decision is allowed to differ from the previous decision when behavioral, cultural, situational, or response information changes.

6.2. Adaptive Cultural Intelligence

The latent computational layer ACI_t (Adaptive Cultural Intelligence) combines behavioral and contextual information:

$$ACI_t = \sigma(W_B B_t + W_C C_t + W_X X_t + W_R R_{t-1} + b)$$

Here, $\sigma()$ is a bounded activation or calibration function, the W terms are learned weights, and b is an intercept. In a machine-learning implementation, ACI_t may be implemented through a supervised model, embedding model, graph model, or hybrid recommender. In a managerial implementation, it can be represented by a weighted score. The important theoretical point is that cultural context is an explicit input rather than an afterthought.

6.3. Context-Aware Adaptation Engine

The Context-Aware Adaptation Engine (CAE_t) translates ACI_t into a candidate set of merchandising actions while applying cultural, operational, ethical, and inventory constraints. Conceptually:

$$CAE_t = g(ACI_t C_t, S_t, M_t^{\text{candidate}}, \text{constraints}_t)$$

The candidate set may include changes in product adjacency, facings, shelf position, visual display, signage language, promotional emphasis, digital recommendation order, or navigation cues. Cultural adaptation should be expressed as compatibility or relevance, not as deterministic assumptions about individuals.

6.4. Spatial optimization with QAP

For shelf, aisle, or planogram decisions, CAMI-DM treats spatial merchandising as an assignment problem. Let i and j index products or categories, k and l index locations, $F_{ij,t}$ be a behavioral flow or affinity between products i and j , D_{kl} be the distance between locations k and l , and $U_{ik,t}$ be the expected utility of assigning product i to location k after cultural and behavioral adaptation. Let $x_{ik,t}$ equal 1 when product i is assigned to location k and 0 otherwise. The proposed optimization is:

$$M_t^* = \arg \min_x \left[\sum_{i,j,k,l} F_{ij,t} D_{kl} x_{ik,t} x_{jl,t} - \eta \sum_{i,k} U_{ik,t} x_{ik,t} \right]$$

subject to one-to-one assignment and capacity constraints, with $x_{ik,t} \in \{0,1\}$. The first term represents flow-weighted movement or interaction cost; the second term rewards culturally and behaviorally relevant placements. The distance matrix should satisfy the metric property $D_{kl} \leq D_{km} + D_{ml}$ for all feasible locations k , l , and m . The triangle inequality is therefore used as a consistency condition on the spatial metric, not as a claim that the resulting planogram is automatically optimal.

This formulation creates a clear division of labor. Machine learning or analytics estimates F and U ; the cultural ontology informs U and adaptation constraints; the QAP solves the spatial assignment layer;

and observed responses feed the next cycle. The approach also permits direct comparisons between a conventional objective function and an adaptation-aware objective function.

7. Testable Propositions and Hypotheses

Table 6: Research Hypotheses, Structural Relationships, and Theoretical Foundations of the CAMI-DM Framework

Hypothesis	Path	Rationale
H1	$PBD \Rightarrow ACI$	Higher-quality and more relevant behavioral signals improve the adaptive system's ability to infer actionable consumer context.
H2	$CCR \Rightarrow CAE$	A richer representation of cultural context improves contextual relevance of merchandising actions.
H3	$SAR \Rightarrow CAE$	Seasonality, store load, channel, and local context improve adaptation when incorporated alongside cultural information.
H4	$Feedback \Rightarrow ACI$	Observed prior responses improve subsequent adaptive intelligence through model updating.
H5	$ACI \Rightarrow CAE$	Stronger adaptive cultural intelligence improves the consistency between inferred context and merchandising actions.
H6	$CAE \Rightarrow CX$	Greater contextual relevance of merchandising improves customer experience.
H7	$CX \Rightarrow Trust$	A more contextually appropriate experience improves trust and perceived value, subject to privacy and transparency conditions.
H8	$CAE \Rightarrow BR$	Greater contextual relevance of merchandising actions directly improves consumer behavioral response, including engagement, purchase intention, or purchase probability.
H9	$TRUST \Rightarrow BR$	Higher trust and greater perceived control strengthen favorable consumer responses to AI-mediated merchandising.
H10 (moderation)	$CAE \Rightarrow CX \Rightarrow TRUST \Rightarrow BR$ (Mediation by CX and TRUST)	The effect of merchandising contextual relevance on behavioral response can be indirectly transmitted through improved customer experience and enhanced trust.
H11 (moderation)	$ACI \times CCR \Rightarrow BR$	The effect of adaptive cultural intelligence on behavioral response varies according to the consumer's cultural-context representation.

8. Empirical Validation Agenda

The systematic review does not empirically test H1–H11. They are propositions derived from the synthesis and should be validated in a subsequent field or experimental study. A suitable design is a two-condition comparison between conventional merchandising and culturally adaptive merchandising, with random assignment where feasible. The target setting can combine physical-store observation with digital interaction data so that perceptual measures from a questionnaire are linked to behavioral and commercial indicators.

8.1. Measurement model

For a subsequent PLS-SEM study, behavioral-data quality (PBD), AI adaptiveness (AIA), cultural-context representation (CCR), situational adaptation (SAR), customer experience (CX), trust/perceived control (TRUST), and behavioral response (BR) can be operationalized as reflective or formative constructs depending on their theoretical definitions. Items should be adapted from validated scales and pretested in the target population. The measurement assessment should report indicator reliability, internal consistency, convergent validity, discriminant validity, and collinearity diagnostics. SmartPLS documentation currently summarizes common benchmarks such as outer loadings around 0.70 or above, $AVE \geq 0.50$, $HTMT \leq 0.85$ as a conservative criterion, and $VIF \leq 3$ as a common target; these are guidelines rather than mechanical acceptance rules (SmartPLS, 2026).

8.2. Classical versus culturally adaptive conditions

A controlled scenario experiment can compare a standard merchandising condition with a culturally adaptive condition while holding prices, availability, product quality, store size, and promotional budget constant. The manipulation should vary only the elements justified by the cultural adaptation logic, such as product adjacency, visual context, signage, language, or recommendation ordering. Manipulation checks should verify perceived relevance and authenticity without inducing demand characteristics. Consumer autonomy should remain explicit: participants should be free to ignore, reject, or override recommendations.

8.3. Multi-group and predictive analysis

When comparing culturally distinct groups, measurement invariance should be examined before interpreting between-group path differences. MICOM followed by an appropriate multigroup analysis can be used in SmartPLS. Out-of-sample predictive performance should also be evaluated, for example with PLSpredict, rather than relying only on in-sample explanatory power (SmartPLS, 2026).

8.4. Outcome variables

Table 7: Outcome Families and Candidate Measures for Evaluating the CAMI-DM Framework

Outcome family	Candidate measures
Behavioral	Conversion, purchase probability, basket composition, repeat visit, dwell time, path length, recommendation acceptance.
Experience	Perceived relevance, cognitive ease, emotional response, satisfaction, perceived personalization.
Relational	Trust, perceived transparency, perceived control, privacy concern.
Commercial	Average basket value, sales by category, cross-selling, revenue per visit, margin contribution, ROI.
Spatial	Walking distance, aisle congestion, product visibility, adjacency quality, travel cost.
Equity/ethics	Disparate recommendation exposure, unnecessary profiling, opt-out availability, perceived autonomy.

9. Discussion

The literature synthesized in this review suggests that the central challenge is no longer whether retailers can personalize. The challenge is whether personalization can remain contextually appropriate when consumers, products, channels, and situations change. The included studies provide a strong empirical and conceptual basis for each component of that challenge but stop short of a unified architecture. The CAMI-DM framework addresses the fragmentation by treating behavioral signals, cultural context, and situational context as joint determinants of an adaptive merchandising state.

The framework also changes how culture is conceptualized in retail analytics. Rather than coding a consumer by nationality and applying a fixed cultural rule, CAMI-DM proposes a multidimensional representation that can include values, beliefs, language practices, symbolic preferences, seasonal patterns, local product affinity, digital behavior, and explicit feedback. Such a representation is closer to the way contemporary multicultural markets operate and better aligned with the need for dynamic updating. It also creates a methodological requirement: cultural variables must be measured or inferred transparently and validated rather than assumed from demographic labels.

The QAP component extends the framework from recommendation to physical decision making. Traditional AI personalization can decide which product or message is relevant to whom, but a store also has to decide where products should be placed, which products should be adjacent, and how the arrangement affects travel and interaction costs. QAP provides a mathematically explicit way to connect behavioral flows and spatial distances. The cultural utility term makes it possible to compare a purely efficiency-oriented planogram with one that incorporates contextual relevance. The triangle inequality constraint protects the internal consistency of the distance metric but does not by itself establish commercial superiority.

9.1. Theoretical implications

CAMI-DM contributes to retailing theory by connecting four research traditions that are often separated: consumer-behavior analytics, AI-enabled personalization, cross-cultural consumer research, and spatial/experiential merchandising. It also shifts the role of culture from a descriptive moderator to an actionable input in a decision architecture. Finally, the state-and-feedback formulation turns adaptive merchandising into a sequential decision problem, creating a bridge between static segmentation models and dynamic learning systems.

9.2. Managerial implications

For retailers, the framework suggests that data collection should be organized around decisions rather than around technology acquisition. The relevant question is which signal can improve a merchandising decision and whether the signal is legitimate and sufficiently reliable. Physical stores can combine POS and movement data with carefully designed cultural-context information. Digital retailers can combine browsing, review, and recommendation responses with culturally relevant interface variables. Phygital systems can connect the two. Across all settings, the adaptation engine should preserve customer choice, provide understandable explanations when appropriate, and minimize unnecessary profiling.

For emerging markets, the framework also supports locally grounded experimentation. In a Côte d'Ivoire setting, for example, a research program could compare conventional and culturally adaptive presentation of locally relevant products, language/signage choices, visual conventions, seasonal assortments, and product adjacencies, while measuring customer response and operational effects. Such

work would provide evidence from a context that is underrepresented in the current corpus without assuming that one national profile captures all consumers.

10. Limitations and Future Research

Several limitations should be acknowledged. First, Scopus was the sole bibliographic database used, and the search was limited to scientific articles and reviews published in English. This choice made it possible to establish a focused corpus based on an international bibliographic source widely used for scientific literature reviews. However, relevant studies indexed in other databases or published in other languages may not have been identified. This limitation may therefore introduce a bibliographic coverage bias and restrict the comprehensiveness of the corpus analyzed.

Second, 2026 is an incomplete publication year because the search was conducted in September.

Third, the joint relevance criteria intentionally prioritized studies located at the intersection of AI and data, retail, and culture. This approach produces a focused synthesis, but one that is relatively narrow in scope.

Fourth, three reports could not be retrieved during the eligibility assessment stage and were therefore not included in the final synthesis.

Fifth, the study proposes the CAMI-DM framework but does not yet undertake its empirical validation. Its hypotheses and mathematical components therefore remain to be empirically tested.

11. Conclusion

This review reframes intelligent multicultural merchandising as an integration problem. The screened literature demonstrates that AI and behavioral analytics can support personalization, that cultural context can alter responses to AI and retail environments, and that physical, digital, and phygital merchandising can be increasingly data-driven. What remains fragmented is the end-to-end connection between these elements. The CAMI-DM framework addresses this gap by linking behavioral and contextual sensing, adaptive cultural intelligence, context-aware merchandising, spatial optimization, customer experience, trust, behavioral response, commercial performance, and feedback-driven updating. The QAP formulation provides a specific mathematical layer for physical placement decisions, while the proposed empirical agenda provides a pathway for testing the framework in real retail settings. The framework should be regarded as a research architecture to be validated and refined, not as a claim that cultural adaptation is universally beneficial or that AI should determine consumer choices. Its core objective is to enable context-sensitive retail decision making while preserving measurement rigor, transparency, and consumer autonomy.

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Appendix A. Recommended empirical implementation of CAMI-DM

A practical field implementation can proceed in four phases. Phase 1 develops and validates the cultural ontology with local experts and consumers. Phase 2 integrates POS, loyalty, navigation, recommendation, and contextual data and estimates behavioral-affinity matrices. Phase 3 compares conventional and culturally adaptive merchandising through controlled scenarios or A/B tests. Phase 4 feeds observed outcomes into the adaptation engine and re-solves the spatial assignment problem. The same architecture can be used for a small pilot store or a larger multi-store experiment, provided data governance and consent requirements are respected.

For a Côte d’Ivoire pilot, the ontology can be designed to capture language preference, locally relevant product categories, visual and symbolic conventions, seasonal events, purchase routines, explicit consumer preferences, and belief/religion-related product requirements only where consumers voluntarily provide or where legitimate business processes require them. The objective is not to infer identity from appearance or ethnicity, but to use validated contextual signals to improve relevance and consumer choice.