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Augmented reality and spatial fit uncertainty in online retailing

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ABSTRACT

Augmented Reality (AR) is an emerging technology in e-commerce that facilitates online product evaluation. It enables consumers to project virtual product models into their real-world surroundings in real time using their mobile devices. By improving online product evaluation, AR has the potential to reduce online consumer product uncertainty and thereby increase e-commerce sales. This paper investigates the effectiveness of AR enablement in reducing spatial product fit uncertainty by analyzing a unique dataset of online purchases of AR-enabled and non-AR-enabled products from a multi-channel home interior retailer. The authors' identification strategy exploits a pandemic-related shutdown of offline retail stores to isolate the effect of AR enablement on online sales when the offline channel is unavailable for product evaluation. The authors find that AR enablement can be particularly effective for evaluating and selling larger products, which are associated with higher spatial fit uncertainty. The authors derive channel-related implications for retailers deploying AR and contribute to retail and consumer research by enhancing the nuanced understanding of online consumer behavior when interacting with a new digital technology.

1. Introduction

Augmented Reality (AR) is an innovative technology that enables consumers to project virtual product models into their surrounding real-world environment in real time (Azuma et al., 2001). While AR can be experienced on various stationary (e.g., smart mirrors) and wearable devices (e.g., headsets/smart glasses), we focus on the case when online consumers inspect products, e.g., via their smartphones ("mobile AR"; Flavián et al., 2019; Rauschnabel et al., 2024). By offering an interactive possibility to inspect products online, AR can contribute to retailers' increased efforts in adopting new digital technologies to improve their online customer experience (McKinsey, 2020; Twilio, 2022). About one seventh of the world's population is currently using AR, and accelerated by the COVID-19 pandemic, online retailers' investments in AR grew by 79 % year-over-year from 2019 to 2020 (Wardini, 2022). By embedding virtual product models into consumers' intended usage contexts (e.g., projecting a virtual model of a sofa into its dedicated place in the living room), AR can improve online consumers' product evaluation and thus reduce frictions before purchase and increase sales (e.g., Heller et al., 2019; Hilken et al., 2017; Tan et al., 2022).

However, despite these advantages of AR and growing retailer investments in the technology, the question remains why retailers have not adopted AR at a larger scale yet. Several online retailers have adopted AR, but not necessarily for the entirety of their product portfolio. Among multi-channel retailers, some have adopted AR for some of their products while numerous have not adopted AR at all.[1] An obvious reason could be the high costs associated with the development and maintenance of an AR application and the concomitant uncertainty whether implementing AR pays off financially.[2] Another reason may be concerns regarding potential spillover effects from consumers' real-world environments onto the evaluated products, for instance when a piece of furniture is projected into an untidy room via AR. As consumers' real-world environments are beyond the direct control of retailers, such contextual spillover effects could pose a threat to the effectiveness of AR (Pfaff and Spann, 2023; von der Au et al., 2023).

Yet another likely reason for retailers' reluctance to implement AR is

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[1] While the online retailer Amazon has implemented an AR feature for at least one product in each category of physical products, among multi-channel retailers, AR is mainly prevalent in the categories furniture, consumer electronics, beauty, and fashion (including shoes).

[2] AR implementation costs can amount to $30,000–100,000 for a standard e-commerce application and an additional $500-2000 for each single 3D product model, with ongoing five-digit server costs per year (e.g., Clavax, 2020; Onix Systems, 2020; Triantafillopoulou, 2023).

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the uncertainty regarding AR's product-related effectiveness (Tan et al., 2022), which is unlikely to be uniformly applicable to different types of product attributes. While some product attributes can be easily assessed and thoroughly evaluated online before purchase, others require physical product inspection or actual offline product trial for proper evaluation (Gallino and Moreno, 2018; Pantano et al., 2017). The uncertainty associated with such product attributes poses a threat to online retailers, as consumers may be reluctant to purchase the respective products (Glover and Benbasat, 2010; Hong and Pavlou, 2014). Hence, online retailers may respond with costly countermeasures such as free sampling or lenient return policies (Gallino and Moreno, 2018). Especially for larger products, however, such countermeasures may not be viable and product-related uncertainty may be particularly high, as the true size of larger products can be difficult to evaluate prior to purchase (Klein, 1998; Zeithaml, 1988). Larger products are thus likely associated with a higher uncertainty regarding the spatial fit with their intended usage context. As AR brings together the (virtual) product with its real usage context, the technology can be a promising solution to alleviate consumers' spatial fit uncertainty (SFU), i.e., their uncertainty about a product's spatial fit with its intended usage context. Table 1 illustrates situations in which consumers may experience SFU while making purchase decisions on retailers' websites in different product categories.

Table 1
Purchase situations involving product-related SFU in different product categories.

Product Category	Exemplary Retailers	Exemplary SFU Problems
Home interior	IKEA, Wayfair, Crate & Barrel	• Fitting furniture within room dimensions: e.g., fit of sofa in living room, clothes cabinet in hallway • Positioning of items relative to other objects: e.g., fit of chairs around dining table, dining table in room • Vertical fit and clearance: e.g., hanging lamp from ceiling • Fit against surfaces or within zones: fit of shelf against wall, carpet on floor
Home improvement & outdoor	Home Depot, HomeBase, Wren Kitchens	• Fitting structures within room or area dimensions: e.g., kitchen unit, bathtub in bathroom, workbench in garage • Placing freestanding elements in outdoor spaces: e.g., pond or pool in backyard, trampoline in yard, bed on balcony • Overhead or vertical space fit: e.g., pergola over patio, parasol on terrace • Fit of tall or spreading vegetation: e.g., trees, plants, greenhouse in garden
Consumer electronics & home appliances	BestBuy, Amazon, Lowe's	• Fitting appliances into designated spaces: e.g., refrigerator in kitchen niche, washing machine in utility room • Placing devices onto surfaces: e.g., coffee machine on kitchen counter • Wall-mounted installations: e.g., TV screen on wall • Integrating systems into a room layout: e.g., home theater system in living room
Sports & leisure	Decathlon, Toys R Us, Costco	• Fitting exercise equipment into indoor spaces: e.g., treadmill in basement, fitness tower in home gym • Fitting play structures into children's areas: e.g., playhouse in children's room
Mobility & automotive	BMW, AutoZone, Strolleria	• Fitting vehicles into spaces: e.g., car in garage • Fitting accessories onto or into vehicles: e.g., bike rack on car roof, folded stroller in car trunk

The goal of our research is to examine the effectiveness of AR enablement in spatial product evaluation and its potential to reduce consumers' SFU, thereby increasing online sales of larger products. This translates into the following research question.

> **RQ:** Does AR enablement reduce SFU and thereby increase online purchases of larger AR-enabled products, relative to smaller AR-enabled products and larger non-AR-enabled products?

To evaluate the effectiveness of AR enablement on sales, we analyze a unique dataset of online purchases in the home interior category. The dataset includes both AR-enabled and non-AR-enabled products across various sizes, as well as an exogenous retail store shutdown. This setting enables a precise estimation of AR's effect from a multichannel perspective. A key challenge in measuring AR's effectiveness is in controlling for potential cross-channel interactions – such as consumers evaluating products in store before purchasing them online, or vice versa – which can bias estimates of AR's true impact. To address this, we leverage a natural experiment as identification strategy: the nationwide shutdown of physical retail stores during the COVID-19 pandemic. This event quasi-experimentally removed the offline evaluation channel, compelling consumers to rely solely on online channels for product evaluation and thereby allowing us to isolate the effect of AR-enabled product evaluation.

Moreover, this identification challenge may partly account for the inconclusive evidence regarding the effectiveness of AR in helping consumers evaluate product attributes. We address this gap by examining the mechanisms through which AR enablement influences online sales of larger products during a period when physical retail channels were unavailable. Specifically, we introduce product size as a new moderator and spatial fit uncertainty (SFU) as a new mediator in the AR-sales relationship. Our study contributes to the broader literature on channel management by employing a rigorous identification strategy and enriching the understanding of AR's role in contemporary retailing.

Our findings show that AR enablement is particularly effective in facilitating the evaluation of spatial product attributes. Specifically, we observe that online sales of larger, AR-enabled products increase when consumers could rely solely on the online channel for spatial product evaluation. Notably, this positive AR effect on sales persists even after the offline channel became available again. These results suggest that AR enablement can serve as an effective tool to reduce consumers' SFU during the purchase decision process by enhancing their ability to evaluate products' spatial attributes.

2. Literature review and conceptual background

2.1. Augmented reality in online retailing

Prior research on AR has mainly compared the effectiveness of AR to traditional online product evaluation technologies such as (contextual) product pictures and 3D product models in front of plain backgrounds (e.g., Gatter et al., 2022; Heller et al., 2019; Hilken et al., 2017; Tan et al., 2022) or context-related spillover effects during AR usage (e.g., Pfaff and Spann, 2023; von der Au et al., 2023; Yim and Park, 2019). Yet, there is sparse differentiating evidence on AR's product-related effectiveness (Tan et al., 2022).

As one of the few exceptions, Choi and Choi (2020) and Fan et al. (2020) find that AR can help consumers to learn about and cognitively process experience products more easily. Heller et al. (2019) find that AR enablement increases consumers' contextual processing fluency, resulting in higher decision comfort and WOM intentions for contextual products (i.e., products which need their usage context for proper evaluation). Mishra et al. (2021) find that consumers are more likely to engage in positive word-of-mouth for hedonic rather than utilitarian

AR-enabled products. Pfaff and Spann (2023) find that negative spillover effects from visually complex (e.g., untidy) contexts on consumers' processing fluency, their product quality perceptions and ultimately their purchase intent are attenuated for uniquely designed products. Lastly, Tan et al. (2022) find a positive yet small sales effect of AR, which is more pronounced for less popular as well as high-priced products. See Table 2 for an overview of product-related AR research.

While the aforementioned studies have examined product-related boundary conditions of AR's effectiveness conceptualizing products as a *whole*, nuanced research on AR's effectiveness for different product *attributes* is lacking. This is an important limitation of previous research on AR-enabled product evaluation which this paper tries to address.

2.2. Spatial product fit uncertainty in online retailing

Consumers may find it difficult to assess the fit between certain product attributes and their own preferences – an observation referred to as "product fit uncertainty" (PFU). Especially in online retailing, PFU can arise from the inability of consumers to physically evaluate products before purchase (Hong and Pavlou, 2014). This is due to the spatial separation of consumers from products as well as the temporal separation of the purchase decision from product fulfillment in online settings (Pavlou et al., 2007; Sun et al., 2022).

While some product attributes can be easily assessed and thoroughly evaluated before purchase via the online channel (e.g., the color or measurements of a sofa), others cannot (e.g., the fit of a sofa into a room; Gallino and Moreno, 2018). Such product attributes therefore require physical product evaluation, which is why they are likely associated with a higher PFU if they are encountered in the online channel (Hong and Pavlou, 2014). PFU hence poses a threat to the business model of online retailers, which have reacted with the adoption of several costly countermeasures to enable actual (physical) product evaluation, such as sending product samples before purchase or offering lenient return policies after purchase (Gallino and Moreno, 2018).

However, there are certain product attributes which are hard to evaluate even in offline retailing, where physical product evaluation is generally possible: A product's true size is a physical attribute which can be difficult to evaluate before purchase (Klein, 1998; Zeithaml, 1988), as consumers would need to inspect the product's dimensions in relation to surrounding objects in reality. While a product's size fit with consumers' *own body* can be physically evaluated before purchase rather easily (e.g., apparel, eyewear, jewelry), the contrary is the case for a product's size fit with consumers' *surrounding environment* (e.g., furniture, consumer electronics, home appliances): Consumers can physically inspect the product's dimensions in offline stores, yet only in relation to stylized showrooms rather than the product's intended real-world usage context (e.g., a sofa or TV in the living room at home). On the other hand, when evaluating products in online stores, consumers may be located in the intended usage context (e.g., in the living room at home), yet they lack the physical product in real size. Online retailers may make use of contextual pictures depicting the product in an exemplary usage context, which however still cannot reflect the product's true size in relation to consumers' *real* usage context. In addition to product pictures, retailers usually communicate product measurements; nevertheless, consumers tend to have difficulties in transferring this information to estimate the true size of objects in physical environments (Berg and Lindström, 2021; Loyola, 2018): For instance, searching the product dimensions in the product description and then measuring the intended usage location of the product by hand is not only time-consuming, but this subjective spatial assessment can also be error-prone.[3]

Therefore, a product's spatial fit with its actual usage context can be considered a source of friction to both online and offline purchases (Gallino and Moreno, 2018; Pantano et al., 2017) due to the SFU associated with larger products. Countermeasures, such as sending product samples to consumers' homes or processing returns of already delivered products, can be quite costly for retailers in case of larger products. Similarly, ordering several sizes or versions of larger products for physical spatial fit evaluation and returning non-fitting products can be quite effortful for consumers.

Consequently, there is a need for innovative online product visualization technologies that enable realistic spatial fit evaluation in physical contexts before purchase. Such technologies would have the potential to reduce aforementioned frictions or even substitute physical product evaluation (e.g., Gallino and Moreno, 2018; Huang et al., 2009; Jiang and Benbasat, 2004). AR is such a technology that can be seen as an interface between the virtual world of online shopping and the physical world, as it brings together the (virtual) product and its intended real-world usage context in real time (Pfaff and Spann, 2023; Rauschnabel et al., 2024). By helping consumers visualize products in their actual usage context, AR creates realistic product experiences and authentic simulations of future consumption before purchase (Hilken et al., 2017). Gatter et al. (2022) even speculate about AR as a potential substitute for physical stores, given the benefits it offers online consumers for their product evaluation. By projecting virtual product models into the consumer's real-world context in real time and at real size (e.g., projecting a correctly scaled virtual model of a sofa into the desired place in the consumer's living room), AR has the ability to provide realistic spatial information and thus improve consumers' spatial product evaluation.

Since AR enablement can reduce consumer uncertainty and increase sales (Heller et al., 2019; Sun et al., 2022; Tan et al., 2022), and as providing fit-related information has been associated with similar positive effects (e.g., Gallino and Moreno, 2018; Kim and Forsythe, 2008), we expect AR's aforementioned product evaluation capabilities of "spatialization and contextualization" (Wedel et al., 2020, p. 445) to reduce consumer SFU associated with larger products, leading to higher online sales for larger AR-enabled products compared to smaller AR-enabled products and larger non-AR-enabled products.

Fig. 1 summarizes our expected results and indicates which proposed link is investigated in our paper. Our main analysis is based on the dataset of online purchases of AR-enabled and non-AR-enabled products of a multi-channel home interior retailer, whereas the supplementary mechanism check for SFU was conducted as an online experiment.

3. Empirical analysis

3.1. Identification strategy and empirical context

When analyzing the effectiveness of AR in online retailing, there is the identification challenge that consumers may additionally evaluate products in offline channels. For instance, if a consumer evaluates the spatial attributes of a product in an offline store before re-evaluating the product online via AR and subsequently purchases the corresponding product online (i.e., "showrooming"; Gensler et al., 2017), the effectiveness of AR enablement would be overestimated, as the prior offline product evaluation may have already substantially contributed to the consumer's reduction of SFU. Conversely, if a consumer first evaluates a product's spatial attributes online via AR and then purchases the product offline (i.e., "webrooming"; Flavián et al., 2016), the effectiveness of AR enablement would be underestimated, as the use of AR may have already played a large role in reducing the consumer's SFU. Accounting for these potential misattribution effects, arising from the coexistence and potential interaction of online and offline channels, is crucial when evaluating the effectiveness of AR enablement for online product evaluation.

To assess the effectiveness of AR enablement, we analyze a unique sales dataset provided by a Western European, multi-channel home

[3] Highlighting the importance of our investigation of product size, uncertainty could potentially also arise from consumers' perception of product mobility, such that larger immobile items (e.g., sofas) may be associated with higher SFU than smaller movable ones (e.g., desk lamps).

Table 2
Product-related AR research.

Paper	Product Attribute Focus	Multi-channel Focus	Channel Identification [a]	Product Boundary Condition	Method	Product Category	Theoretical Lens	Main Findings
Choi and Choi (2020)	no	no	n/a	Product type (search vs. experience)	Online experiment	Electronics (search) vs. home interior (experience)	Experience economy, task-media fit	AR enablement can improve consumer learning and increase purchase intentions. Effect is stronger for experience products.
Fan et al. (2020)	no	no	n/a	Product type (search vs. experience)	Lab experiment	Electronics (search) vs. cosmetics (experience)	Cognitive load and fluency	AR's ability to embed products into their usage context increases cognitive fluency for experience products.
Heller et al. (2019)	no	no	n/a	Product contextuality (Study 3, 4)	Online experiments	Home interior (contextual) vs. food (non-contextual)	Mental imagery, processing fluency, style of processing	AR enablement facilitates processing fluency, resulting in higher decision comfort and WOM intentions for contextual products.
Mishra et al. (2021)	no	no	n/a	Product type (hedonic vs. utilitarian)	Lab experiment (Study 2)	Home interior	Vividness	AR enablement is more effective for hedonic products when it comes to increasing the likelihood of positive word-of-mouth.
Pfaff and Spann (2023)	no	no	n/a	Product design uniqueness (Study 1, 3)	Online experiment (Study 1), field study (Study 3)	Home interior	Perceptual and conceptual processing fluency	Visually complex AR contexts inhibit fluent processing, reducing perceived product quality and purchase intentions. Effect is mitigated for AR products of unique design.
Tan et al. (2022)	no	yes	no	Product popularity/ appeal, price, rating	Quasi-experiment	Cosmetics	Product fit uncertainty	Positive yet small sales effect of AR enablement is more pronounced for niche/long-tail as well as high-priced products.
This paper	*yes*	*yes*	*yes*	Product size (volume)	Quasi-experiment	Home interior	Spatial fit uncertainty	AR enablement reduces spatial fit uncertainty, especially for larger products, with effects persisting even after offline channel reopens.

Note: [a] Applies only to studies with multi-channel focus.

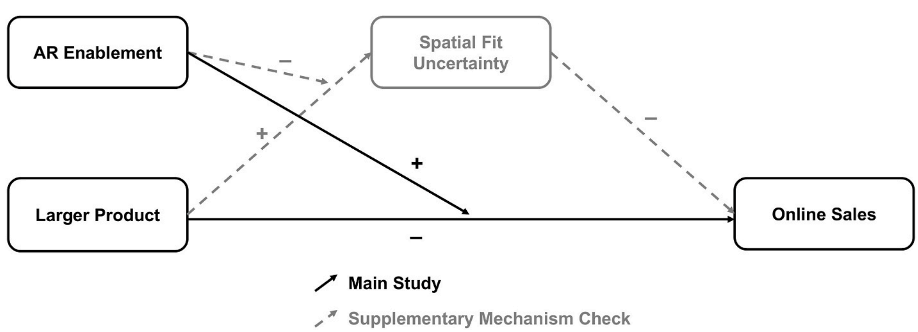

Fig. 1. Conceptual framework.

interior retailer. The data includes purchases of AR-enabled and non-AR-enabled products from the retailer's online store in a Western European country. To identify and isolate the AR effect, we make use of a nationwide shutdown of retail stores during the COVID-19 pandemic as an exogenous event. The shutdown deprived consumers of the ability to physically evaluate products in the offline channel, leaving them with the ability to evaluate products via the online channel only. This identification strategy allows us to approximate the "net AR effect" more closely than in a situation where the offline channel and its content characteristics (such as sales staff support) exists as a parallel opportunity for product evaluation.

In the country we study, the shutdown included in our observation period lasted for four weeks in the spring of 2020. During the shutdown, only "essential" stationary retail such as pharmacies, drugstores, and grocery stores were allowed to remain open. All "non-essential" stationary retail, including the stores of the focal retailer, had to remain closed. Thus, this situation allows us to compare sales in the time period before the shutdown (both online and offline channels available for product evaluation) with the period during the shutdown (only online channel available) and after the shutdown (again both channels available) for AR-enabled and non-AR-enabled products and their spatial attributes (see Fig. 2).

The retailer owns more than 200 stores in 50 countries worldwide, with around 30 offline stores in the focal country. Importantly, the retailer has an AR feature implemented in its online store in the focal country (see Fig. 3 for an illustration). With the AR function, consumers

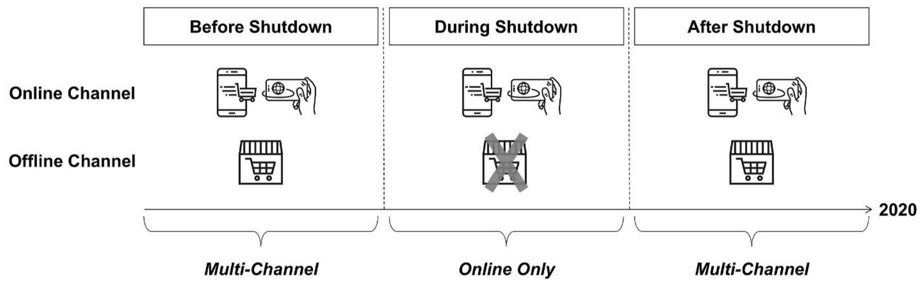

Fig. 2. Identification strategy.

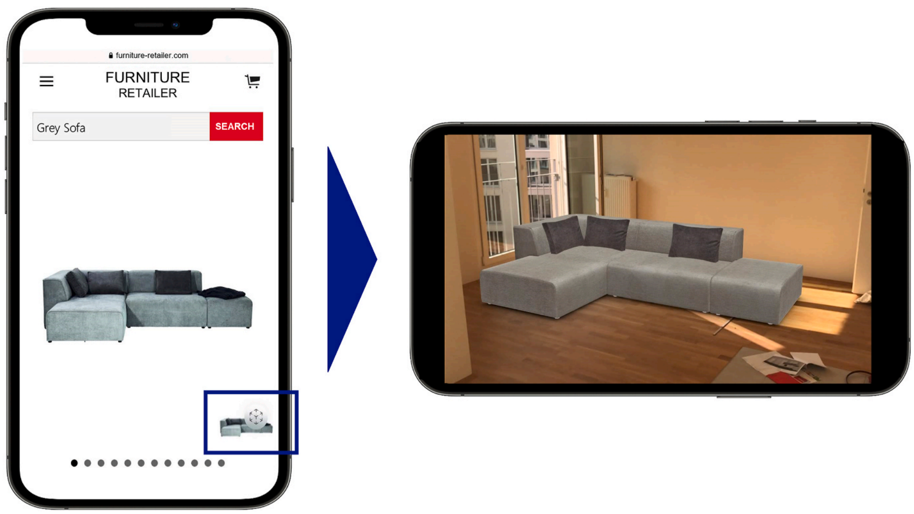

Fig. 3. Illustration of AR feature in Retailer's online store.

can move and rotate high-quality 3D models of AR-enabled products, placing them in their desired surroundings at the correct size with accurate color representation.[4] The retailer sells its proprietary brand of furniture only, which means that consumers cannot purchase third-party brand products from the retailer, nor can they purchase or evaluate the retailer's products at other retailers. The retailer charges shipping fees based on the type of delivery, which is related to the size of the products.

3.2. Dataset description

The dataset we obtained from the focal retailer includes the sales of 2489 unique products observed over a period of 82 weeks, including the shutdown. Our data are thus at the product-week level, yielding a total of 99,986 observations. The dataset is structured as an unbalanced panel, as we can only observe products once they appear in the dataset for the first time due to a purchase. Our observation period spans 64 weeks before, 4 weeks during, and 14 weeks after the shutdown.

In addition to sales data, the dataset includes information on AR enablement as well as other product characteristics, such as measurements, price, category, color, material, the number of images with which the products are presented in the retailer's online store, product-related badges which highlighted certain products, as well as the communicated usual delivery time for a specific product (see Table 3 for an operationalization of our variables and corresponding descriptive statistics; see Web Appendix A for a correlation matrix).[5]

We observe a strong heterogeneity in sales quantity, ranging from products that were not purchased at all in certain weeks to products that were purchased up to 103 times per week. Products' AR enablement is indicated by 1 if the respective product is AR-enabled, and zero otherwise. In our dataset, 1116 (45 %) different products (comprising 53,009 or 53 % of observations) are equipped with an AR function. To identify the "net AR effect" arising from the closure of offline stores, the four-week period in which the shutdown occurred is indicated by 1, and zero otherwise. Similarly, the time period after the shutdown is indicated by 1, and zero otherwise.

We also observe a strong heterogeneity regarding product size, ranging from very small to rather large products in terms of volume.[6] The same applies to product prices, which range from € 0 to more than € 3000. Prices are adjusted for order-specific coupons and shipping fees in a value-based manner, i.e., we distribute the monetary value of coupons and shipping fees per order across all products from the same order, based on their share of the total product-related monetary value of the order. We logarithmize both product volume and prices due to their non-normal distributions.

The products in the dataset can be segmented into four broad categories: furniture, accessories (e.g., carpets, vases, and other decorative items), lamps, and mirrors, with the furniture category having the highest number of AR observations (see Table 4 for a category overview).

We observe 19 different basic colors of products (ranging from darker colors like black and brown to lighter colors like beige and white)

[4] Note that all 3D models of AR-enabled products were developed by the same design agency. Hence, the 3D models are standardized across AR-enabled products with no quality differences.

[5] Note that the retailer does not provide other product attribute cues, such as additional product descriptions or product reviews.

[6] "Size" and "volume" refer to a product's three-dimensional measurements when it is fully assembled. These product measurements are indicated on each respective product detail page and are thus visible to consumers before purchase.

Table 3
Variable operationalization and descriptive statistics.

Variable	Operationalization	*M*	*SD*	Min	Max
$Sales_{it}$	Online units sold per product *i* in week *t*	.37	1.76	.00	103.00
AR_i	= 1 if product is AR-enabled, zero otherwise	.53	.50	.00	1.00
$Online\ Only_t$	= 1 if shutdown was in effect, zero otherwise	.06	.24	.00	1.00
$After_t$	= 1 if after shutdown, zero otherwise	.16	.36	.00	1.00
$Volume_i$	Log of product volume (in m^3)	.22	.32	.00	2.10
$Price_{it}$	Log of product price, adjusted for coupons and shipping fees (in €)	5.03	1.33	−12.76	8.10
$Images_i$	Number of images used to present product	7.72	4.07	1.00	50.00
$Bestseller_i$	= 1 if product was labelled as “Bestseller”, zero otherwise	.12	.33	.00	1.00
$Discount_{it}$	= 1 if product was on discount, zero otherwise	.24	.43	.00	1.00
$Campaign_{it}$	= 1 if product was part of special campaign, zero otherwise	.05	.23	.00	1.00
$Delivery\ Time_i$	Communicated usual product delivery time (in weeks)	2.19	2.24	1.00	7.00
$Time\ on\ Market_{it}$	Product’s time on the market in current week, measured from first week of appearance in dataset	29.94	20.61	.00	81.00
$COVID\ Cases_t$	Number of COVID-19 cases per week in focal country	494.74	1,224.48	.00	5,152.43
$COVID\ Containment\ Index_t$	Index of COVID-related policy strictness per week in focal country	19.09	28.58	.00	76.52

Table 4
Overview of product categories and AR enablement.

Product Categories	Total Obs.	Share of Total Obs.	AR Obs.	Share of AR Obs.	Within-Category AR Share
Furniture	46,207	46.21 %	32,731	61.75 %	70.84 %
Accessories	40,755	40.76 %	11,319	21.35 %	27.77 %
Lamps	8,909	8.91 %	5,785	10.91 %	64.93 %
Mirrors	4,115	4.12 %	3,174	5.99 %	77.13 %
Total	*99,986*	*100.00 %*	*53,009*	*100.00 %*	*53.02 %*

and nine different main materials (such as textile, wood, glass, and stoneware). Products are presented in the online store with as little as one image and up to 50 images. Various products were promoted by “Bestseller”, “Discount”, and campaign-specific badges (i.e., during “Black Friday Week”). The communicated usual delivery time for specific products ranges from one week to seven weeks.

We calculate a product’s time on the market (i.e., time elapsed from the product’s first appearance in the dataset up to the current week) as a proxy for consumer familiarity with the product. The latter is based on the rationale that the longer the product has been on the market, the more likely it is that consumers may have become familiar with the product.

To account for COVID-related circumstances that might have influenced consumers’ shopping behavior, we added weekly COVID-19 cases in the focal country to our dataset, which range from zero to more than 5000 cases at the peak of the pandemic included in our observation period. In addition, we include the COVID-19 Containment and Health Index calculated by the Oxford Coronavirus Government Response Tracker project. This index is a composite measure of 13 metrics reflecting the stringency of COVID-related policies such as movement restrictions, face mask requirements, contact tracing, testing and vaccination policies, as well as “soft” policies such as public information campaigns.[7] Index values can range from 0 to 100, with higher scores indicating stricter government responses.

3.3. Model specification

We examine changes in the weekly sales quantity for AR-enabled and non-AR-enabled products as a function of their spatial attributes before, during, and after the shutdown of the offline channel (Equation (1)). For our analysis, we use $Sales_{it}$ as dependent variable. $Sales_{it}$ is an over-dispersed[8] count variable characterized by a long-tailed distribution and composed exclusively of non-negative integer values (Cameron and Trivedi, 2013). To account for this overdispersion, we estimate a random-effects negative binomial panel model, in line with approaches used for AR sales data (e.g., Tan et al., 2022). This model is particularly well-suited for our data structure and variable characteristics. Furthermore, based on goodness-of-fit tests following Rietveld et al. (2022), we find the negative binomial model to outperform alternative count models, such as the Poisson model, as indicated by superior Log Likelihood, AIC, and BIC values (see Web Appendix C). As independent variables, we use the binary indicators AR_i for a product’s AR enablement, $Online\ Only_t$ for the closure of offline stores, and $After_t$ for the time period after the shutdown.[9]

$$\mathrm{Sales_{it}} = \beta_0 + \beta_1\,\mathrm{AR_i} + \beta_2\,\mathrm{Volume_i} + \beta_3\,\mathrm{Online\ Only_t} + \beta_4\,\mathrm{AR_i} \times \mathrm{Volume_i} + \beta_5\,\mathrm{AR_i} \times \mathrm{Online\ Only_t} + \beta_6\,\mathrm{Volume_i} \times \mathrm{Online\ Only_t} + \boldsymbol{\beta_7\,\mathrm{AR_i} \times \mathrm{Volume_i} \times \mathrm{Online\ Only_t}} + \beta_8\,\mathrm{AR_i} \times \mathrm{After_t} + \beta_9\,\mathrm{Volume_i} \times \mathrm{After_t} + \boldsymbol{\beta_{10}\,\mathrm{AR_i} \times \mathrm{Volume_i} \times \mathrm{After_t}} + \beta\,\mathbf{X_{it}} + \sum_{w=1}^{T-1} \delta_w\,\mathrm{week_t} + \varepsilon_{it}. \quad (1)$$

Our coefficients of main interest are thus β_7, indicating the isolated AR sales effect for larger products when only the online channel is available for product evaluation ($AR_i \times Volume_i \times Online\ Only_t$), as well as β_{10}, indicating the potential persistence of the AR sales effect for larger products when the offline channel becomes available again for product evaluation ($AR_i \times Volume_i \times After_t$).

In a vector of control variables, we account for $Price_{it}$, $Product\ Category_i$, other product characteristics ($Color_i$, $Material_i$, $Images_i$) and product-related badges ($Bestseller_i$, $Discount_{it}$, $Campaign_{it}$). We also control for $Delivery\ Time_i$ to account for the possibility that a distant delivery time may discourage consumers from purchasing the respective product and make them look for alternatives (Balakrishnan et al., 2014). Categorical variables such as $Product\ Category_i$, $Color_i$, and $Material_i$ are included in our model in factor notation.

In addition, we control for $Time\ on\ Market_{it}$, as the longer a product has been on the market, the more prior experience consumers may have had with the product and the less likely it is that product evaluation via AR provides additional diagnostic information to potentially reduce SFU (Hong and Pavlou, 2014).

Moreover, we include $COVID\ Cases_t$ and the $COVID\ Containment\ Index_t$ to capture general consumer uncertainty and other potential COVID-related influences on consumer behavior beyond the shutdown. Finally, we include week fixed effects (for t = 1, …, T weeks) to control for unobservable time effects.

[7] See https://ourworldindata.org/covid-stringency-index for more details.
[8] The variance of $Sales_{it}$ is nearly 10 times larger than its mean (M = .372, variance = 3.091). See Web Appendix B for the distribution of $Sales_{it}$.

[9] Interactions of $After_t$ allow us to separate effects of the pre-pandemic period (before the shutdown) from the reopening period (after the shutdown), as we do not assume that consumer behavior in the reopening period will revert to the pre-pandemic situation.

Table 5
Kernel propensity score matching.

Variable	Condition	*M* AR (Treatment)	*M* Non-AR (Control)	*t* $p > \|t\|$	Bias Reduction
Price	Unmatched	500.15	220.22	17.73 .000	95.7 %
	Matched	485.91	498.04	−.62 .535	
Volume	Unmatched	.44	.21	9.00 .000	97.9 %
	Matched	.43	.42	.16 .876	
Bestseller	Unmatched	.14	.02	11.26 .000	70.0 %
	Matched	.13	.10	2.56 .011	

Note: Mean bias of sample = 49.7 % (unmatched) vs. 5.6 % (matched).

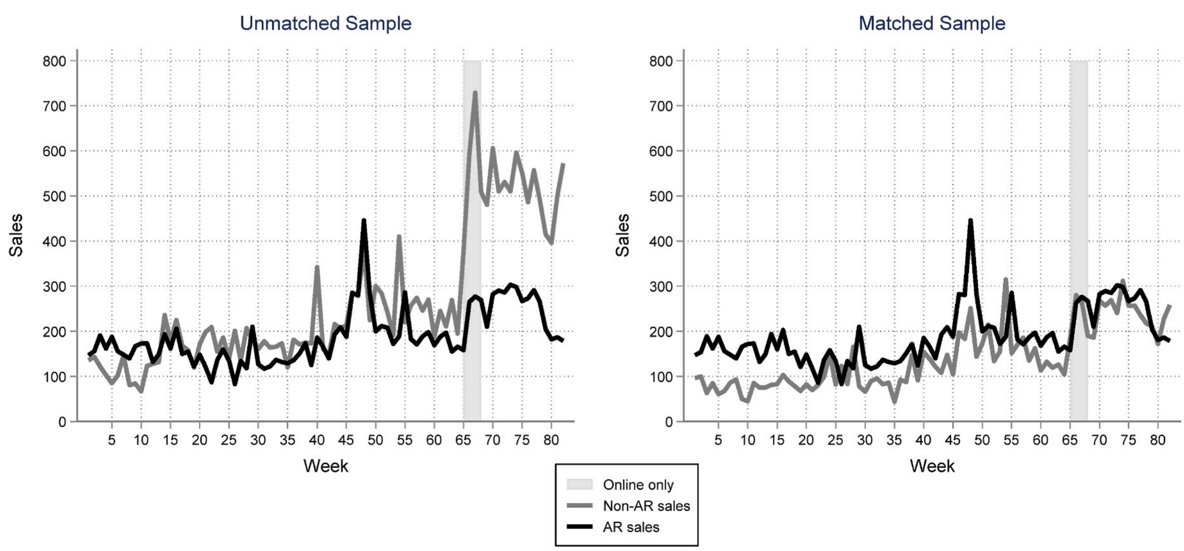

Fig. 4. Comparison of parallel trends for matched and unmatched samples.
Note: Matched sample is based on kernel propensity score matching.

3.4. Matching

As the choice of which products in the online store are equipped with an AR function may be endogenous, we matched AR-enabled products with similar non-AR-enabled products using kernel propensity score matching (Rosenbaum and Rubin, 1983). We matched on product prices, volume, and whether products are highlighted with a "bestseller" badge[10]. This significantly reduced the bias between the treatment and control groups. Matching thus increases the comparability between AR-enabled and non-AR-enabled products in terms of key variables (see Table 5), covariates (see Web Appendix D), and sales trends before and during the shutdown (see Fig. 4).

3.5. Results

The results of our negative binomial panel regression model are presented in Table 6. We present results for the unmatched as well as the kernel propensity score matched samples.

We find a positive and significant effect of *AR*, indicating that AR enablement seems to have a generally positive effect on online sales. The significant negative coefficients of *AR* × *Volume* may indicate that consumers seem to generally prefer buying larger products offline, despite their AR enablement. However, these two estimates reflect the simultaneous availability of both the online and the offline channel. Hence, one cannot preclude the aforementioned possibility that consumers might have evaluated products in store before or after their online product evaluation via AR, which could lead to a misestimation of the focal AR effect.

When consumers are deprived of the opportunity to physically evaluate products in the offline channel, AR enablement does not seem to uniformly satisfy consumers' evaluation needs (significant negative coefficients of *AR* × *Online Only*). In addition, consumers still seem to be reluctant to purchase larger products online when only the online channel is available for product evaluation (negative, yet non-significant coefficients of *Volume* × *Online Only*). However, if the larger products are AR-enabled when only the online channel is available, there is a positive effect of AR enablement on online sales of larger products (significant positive coefficients of *AR* × *Volume* × *Online Only*). Thus, AR enablement can be seen as particularly effective in improving consumers' spatial product evaluation, as it increases online sales of larger products.

Specifically, a floodlight analysis using the Johnson-Neyman technique (Johnson and Neyman, 1936; Spiller et al., 2013) reveals that the positive effect of AR enablement emerges only for products with

[10] Personal Correspondence with the retailer indicated that "bestseller" products might have been more likely equipped with an AR function. We are not aware of any extra communication activities by the retailer with the goal of advertising the AR function to consumers.

Table 6
Effect of AR enablement on online sales.

	(1)	(2)
Sales	Unmatched	Matched (Kernel Propensity Score)
AR	.244***	.236***
	(.043)	(.044)
Volume	.161	.104
	(.116)	(.098)
Online Only	21.578***	21.844***
	(.436)	(.475)
AR × Volume	−.341***	−.268***
	(.116)	(.102)
AR × Online Only	−.361***	−.250***
	(.069)	(.080)
Volume × Online Only	−.151	−.170
	(.167)	(.160)
AR × Volume × Online Only	**.481****	**.496****
	(.198)	**(.193)**
AR × After	−.187***	−.175***
	(.042)	(.048)
Volume × After	.031	−.033
	(.099)	(.092)
AR × Volume × After	**.296****	**.396*****
	(.120)	**(.114)**
Constant	.242*	.459***
	(.127)	(.137)
ln(r)	1.701***	2.071***
	(.041)	(.047)
ln(s)	.962***	1.115***
	(.043)	(.049)
Controls	Included	Included
Week Fixed Effects	Included	Included
Observations	99,986	99,690
Products	2489	2481
Chi-Square	9480	7920
Prob > Chi-Square	.000	.000
LogLikelihood	−61,509	−51,215
AIC	123,281	102,692
BIC	124,527	103,938

Note: *$p < .1$, **$p < .05$, ***$p < .01$. Standard errors (observed information matrix) in parentheses.

(non-logarithmized) volumes exceeding 1.65 m^3. This finding underscores the heterogeneous impact of AR enablement across different product sizes (see Web Appendix E for the corresponding Johnson-Neyman plot). Based on a simple cost-benefit analysis using conservative estimates of AR enablement costs as outlined in the introduction,[11] we estimate that the home-interior retailer could have increased profits by 12 % by limiting AR investments to products for which AR enablement proved effective, i.e., those with volumes greater than 1.65 m^3.

The positive AR sales effect for larger products does not seem to be of only temporary nature during the shutdown. AR enablement still satisfies consumers' evaluation needs for larger products, as there is a significant positive effect on online sales of larger AR-enabled products after the shutdown (*AR* × *Volume* × *After*). Again, this positive AR effect does not uniformly apply to products of various sizes (significant negative coefficients of *AR* × *After*), yet only to larger products. Fig. 5 visualizes the key results.

To test our theorized mechanism, spatial fit uncertainty SFU, we conducted a supplementary online experiment. The results provide empirical support for the pivotal role of AR in reducing consumers' SFU, which in turn increases their purchase intention for larger products. Full methodological details and results are presented in Web Appendix F.

Taken together, our findings suggest that AR enablement can be an effective tool for reducing consumers' SFU by facilitating the evaluation of spatial product attributes. We observe that online sales of AR-enabled products increase when consumers are restricted to the online channel for spatial evaluation. However, this positive AR effect is not uniform across all product sizes; it is particularly pronounced for larger products, which are more likely to elicit higher SFU. Notably, the effectiveness of AR persists even after the offline channel becomes accessible again. This indicates that once consumers become familiar with AR and its benefits, they may continue to prefer AR for spatial product evaluation, consistent with the notion of channel learning and adaptation (Melis et al., 2015).

3.6. Robustness checks

We demonstrate the robustness of our results by assessing alternative specifications of our model, identification strategy, and matching approach (Web Appendix G and Web Appendix H).

To address potential concerns about model dependency, we re-estimate our negative binomial panel model with a fixed-effects specification (Web Appendix G.1) and an alternative random-effects OLS panel model (Web Appendix G.2). To this end, we logarithmized the sales variable to transform its count data into non-integer numbers and approximate normal distribution.

Furthermore, we test the robustness of our identification strategy by replacing the binary $Online\ Only_t$ indicator in our original random-effects negative binomial panel model with a continuous $Residential_t$ variable and thereby incorporate consumer mobility behavior during our observation period (Web Appendix G.3). Data was gathered from Google's Community Mobility Reports[12] and the variable reflects weekly movement trends for our focal country relative to the median value of residential movements from the 5-week period January 3 to February 6, 2020. More specifically, $Residential_t$ indicates the average duration spent in places of residence (in hours) rather than in e.g., retail stores, transit stations, workplaces, or parks.

To assess the independence of our findings from the underlying specification of our matching approach, we apply a stricter propensity score matching approach based on the entire range of product-related covariates available in our dataset for comparison (see Web Appendix H).

All of the aforementioned checks yield qualitatively similar results. Hence, we conclude that our findings are robust against alternative specifications of our model, identification strategy, and matching approach.

4. General discussion

4.1. Theoretical contribution

Our paper contributes to retailing and consumer research in several important ways. In line with prior studies on AR's product-related effects (e.g., Gatter et al., 2022; Heller et al., 2019; Hilken et al., 2017; Tan et al., 2022), we show that the effectiveness of AR enablement varies depending on specific product characteristics. By focusing on product attributes and introducing product size as a novel boundary condition, we advance the understanding of when and for which products AR is most effective in online retail settings. This extends previous AR research that conceptualizes products as a *whole*.

Moreover, we introduce and empirically test a novel mediator, spatial fit uncertainty (SFU), in the relationship between AR enablement

[11] In our calculation, we assume a one-time AR enablement cost of $500 per product; the creation of a single 3D product model for AR can cost $500 to $2000 (e.g., Clavax, 2020; Onix Systems, 2020; Triantafillopoulou, 2023).

[12] https://www.google.com/covid19/mobility/?hl=en.

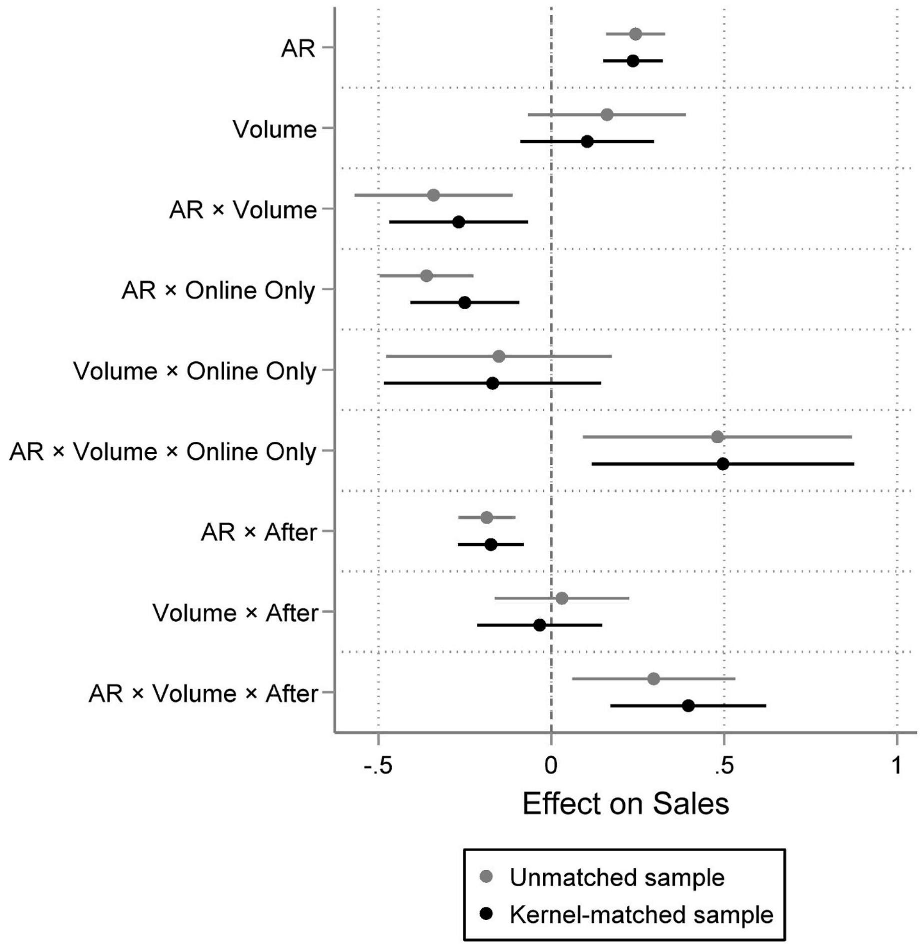

Fig. 5. Visualization of key results.
Note: Error bars depict 95 % confidence intervals. Coefficient of *Online Only* not included in visualization due to its proportionally large effect size.

and sales. In doing so, we deepen the understanding of AR's influence on consumer behavior, complementing prior research that has primarily focused on perceptual, cognitive, or media-related psychological mechanisms.

Additionally, we leverage a pandemic-related retail shutdown as a natural experiment to more precisely identify the "net AR effect." During this period, consumers were unable to assess products through offline channels, allowing us to isolate the impact of AR in the absence of physical product evaluation.

Finally, our study is the first to examine AR from a multi-channel perspective, offering new insights into how consumers evaluate spatial product attributes across online and offline contexts. This contributes to a more comprehensive understanding of AR's role in cross-channel retail environments.

4.2. Managerial implications

Our results have several implications for retailers beyond the home interior category based on the retail channels in which they are active.[13] In general, retailers should prioritize integrating AR across their product portfolios associated with a high SFU (i.e., larger products) and highlight the availability and benefits of AR to consumers (e.g., by placing a prominent "Try in your room" button on product detail pages). To promote further AR usage, retailers could raise awareness of AR by offering temporary discounts or loyalty rewards to consumers who use AR to evaluate products during the purchasing process. To appeal to first-time users, retailers should provide clear instructions on how to use the AR function. Additionally, retailers could leverage AR usage data to learn about consumers' room sizes and placement patterns. They could then use these insights for context-aware personalization by recommending related products that fit the same space and are pre-filtered by spatial compatibility.

For pure-play online retailers, our results imply that AR enablement can mitigate the disadvantages of the online channel when it comes to evaluating spatial product attributes. Traditionally, spatial product attributes require up-front physical product trials for proper evaluation, which is not always feasible for larger products in online retailing. To still facilitate spatial product evaluation, online retailers have adopted costly countermeasures such as sending product samples or offering free product returns (Gallino and Moreno, 2018). With AR, online retailers now have a promising technological solution at hand to reduce online consumers' SFU. The technology is certainly not free, but it could be more cost-effective than the aforementioned countermeasures. In order to save on software development and maintenance costs, retailers are well advised to implement AR where it is most effective, namely for larger products.

For pure-play offline retailers, our results imply that their offline advantage in spatial product evaluation may be diminished by the advent of AR. If consumers can properly evaluate spatial attributes online thanks to AR, visiting an offline store to evaluate larger products in real size may become obsolete – especially since AR was found to be

[13] For a differentiation of retailer types and corresponding consumer behavior by channel, see e.g., Verhoef et al. (2015), Gensler et al. (2012), and Ansari et al. (2008).

particularly effective for consumers new to the online channel (Tan et al., 2022). Although offline retailers have real products at real size available, they still face the disadvantage of lacking the consumer's actual usage context for in-store evaluation. A potential solution could be so-called "reverse AR", where consumers first scan their intended usage context (e.g., their living room at home) with their smartphone and then evaluate the real product in the store against the virtual intended usage context in the background (Strange Native, 2022).

Multichannel retailers could benefit from implementing both AR and reverse AR to bridge online-offline gaps for their larger products. Thanks to AR, they would need less warehouse stock and showroom space for physical products as well as fewer sales staff to support consumers in spatial product evaluation in offline stores.[14] Implementing AR in online retail could therefore help save costs in offline retail. On the other hand, implementing reverse AR could be particularly useful for consumers who prefer to evaluate real products in front of virtual usage contexts instead of evaluating virtual products in front of real usage contexts (as with AR). Implementing reverse AR would also allow consumers to evaluate physical product attributes other than spatial ones, such as haptic attributes (e.g., the material and comfort of a sofa) which cannot be adequately evaluated via AR. Thus, AR could enhance retailers' multichannel strategy by providing a more seamless product evaluation experience.

4.3. Limitations and future research

We have to acknowledge limitations of our empirical study, which provide avenues for future research. First, we were not able to obtain customer-related information from the retailer. Thus, the sales we observe in our dataset cannot be linked to individual customers and their AR usage. Therefore, we cannot analyze potential differences in AR's usage frequency and effectiveness for new versus existing online customers, or whether customers with a preference for offline product evaluation switched to the online channel because of AR and the lack of offline evaluation options due to the shutdown. Future research could explore these different customer types and other potential consumer-, retailer- and device-related moderators to address questions like whether consumers prefer retailers offering AR for product evaluation, whether consumers spend more time on the detail pages of AR-enabled products, and whether consumers include a higher number of products in their consideration sets if products are AR-enabled. Investigating specific mechanisms in the AR-SFU relationship, such as cognitive fluency or visualization accuracy, could advance AR research as well.

Second, future research could investigate AR's potential to adequately convey aesthetic product information, thus helping consumers to evaluate style-related product attributes (e.g., unusual colors, shapes, or designs) and their fit with consumers' existing interiors.

Third, we sound a note of caution inferring representativeness from consumer behavior in our observation window (including a single four-week shutdown and 14 weeks after reopening) for consumer behavior under normalcy. As we used a COVID-related shutdown as our identification strategy, one cannot completely rule out potential unobserved influences of the pandemic on our findings. To address these concerns, we included COVID-related control variables lending credibility to our results. Investigating an expanded observation window including subsequent shutdowns, or leveraging a deactivation of the offline channel due to other exogenous events (e.g., temporary store closings due to unexpected maintenance) as an alternative identification strategy, may be worthwhile endeavors for future research.

Fourth, as with any study based on observational data, treatment endogeneity remains a potential concern. However, we address this issue through a quasi-experimental design that leverages an exogenous event for identification. In addition, we apply a matching approach to improve the comparability between treatment and control groups and conduct a series of robustness checks to assess the stability of our findings. These steps collectively enhance our confidence in the validity of the results. Nonetheless, we acknowledge that we cannot fully account for time-varying unobserved factors—such as shifts in consumer interest or exposure to marketing activities beyond the campaign-related product badges included in our data.

Finally, we acknowledge that findings from a temporary channel closure at a multichannel retailer might not entirely generalize to other types of retailers, due to potential differences in consumer behavior. Future research could replicate our analysis with data from a pure-play online retailer, with a comparable pure-play offline retailer as control. Additionally, examining product categories beyond home interior would help assess the generalizability of our findings across different retail contexts.

5. Conclusion

We conducted a detailed analysis of the effectiveness of augmented reality (AR) as an innovative digital technology in online retailing. Specifically, we investigated how AR enablement reduces spatial fit uncertainty (SFU) by supporting consumers in evaluating spatial product *attributes*.

We theorized and empirically tested the relationship between spatial product attributes and online sales, conditional on whether a product is AR-enabled. To identify the causal effect of AR, we leveraged a COVID-related retail shutdown as an exogenous event. This novel identification strategy allowed us to approximate the "net AR effect" more precisely, as consumers were temporarily unable to evaluate products in physical stores. To address potential endogeneity concerns related to AR enablement, we employed a matching procedure to pair AR-enabled products with comparable non-AR-enabled counterparts, thereby improving product-level comparability. Our findings reveal that AR enablement is not uniformly effective for evaluating spatial product attributes. Rather, it is particularly beneficial for larger products, which are typically associated with higher spatial fit uncertainty (SFU).

This research contributes to the broader channel management literature and advances the scholarly discourse on the role of augmented reality (AR) in retailing. It offers channel-specific implications for different types of retailers and identifies promising avenues for future research.

CRediT authorship contribution statement

Alexander Pfaff: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Martin Spann:** Writing – original draft, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jretconser.2025.104442.

Data availability

The authors do not have permission to share data.

[14] See, e.g., Rejeb et al. (2021) for a review of AR's potential in supply chain management.

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