

CRISight: Seeing Cannibalisation Before it Happens

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ABSTRACT

New product sales do not always represent new growth. A new offering can create primary demand, attract customers from competitors, shift purchases across time, or transfer demand from the firm's own products. This article develops CRISight, a proposed pre-launch cannibalisation risk framework that brings these demand sources into one structured decision system. The framework is grounded in established cannibalisation measurement, demand decomposition, brand-extension research, consumer consideration, perceived value, usage occasion, channel access and portfolio branding. It proposes seven core risk dimensions: Customer-Segment Overlap, Internal Switching Propensity, Product and Benefit Similarity, Price and Perceived-Value Proximity, Usage-Occasion Overlap, Channel and Market-Access Overlap, and Brand and Portfolio Proximity. A formative higher-order risk index is proposed, while Evidence Confidence and Strategic Cannibalisation Tolerance are reported separately so that weak evidence or managerial willingness does not artificially change the underlying risk. The paper also clarifies the difference between a pre-launch risk score and a realised post-launch cannibalisation rate. Initial weights should be treated as provisional; final weights, thresholds and category benchmarks require empirical calibration against post-launch demand-source outcomes. A multi-study validation programme is proposed, covering qualitative domain specification, content validation, measurement purification, discrete-choice testing and longitudinal predictive validation. The article contributes an integrated, transparent and testable architecture for moving cannibalisation analysis from retrospective diagnosis towards pre-launch portfolio decision support.

Keywords: cannibalisation; brand extension; line extension; new product development; consumer switching; portfolio strategy; predictive index

INTRODUCTION

Business profit growth is an important priority because it allows firms to remain competitive, strengthen their market position, and support long-term sustainability. One way to achieve this growth is through new product development, particularly as firms need to respond to changing customer preferences, rapid market trends, novelty-seeking behaviour, and fear of missing out (FOMO) (Guiné et al., 2020). Brand and line extensions are particularly attractive since they allow firms to leverage an established brand name, existing distribution channels, and existing customer knowledge. However, a strong launch at the individual SKU level does not necessarily mean a success for the overall portfolio. Some customers may simply switch from an existing product of the firm to the new product rather than creating additional sales. This type of internal change in demand is often called product cannibalisation.

The worry is not that all cannibalisation is bad. There are reasons why a company would want to move customers to a higher margin product, replace an ageing offer, protect its buyers from competitors, or refresh its portfolio. The real managerial problem is that firms often estimate sales of the new product without distinguishing truly

incremental demand from sales drawn from their own products (Okorie et al., 2021). Thus, a launch could seem successful while the total portfolio profit varies little.

Studies of cannibalisation have shown that the problem has to be seen at portfolio level and measured using more than one method (Lomax, 1996; Mason & Milne, 1994). Later demand-decomposition studies show that a sales increase can also be driven by internal switching, competitor switching, category expansion or timing shifts (Van Heerde et al., 2004, 2010). More recent studies explain the possibility of transfer in terms of shared customers, benefits, value positions, usage occasions, channels and brand architecture, but also that a consumer must notice and consider the new product before switching (Abaluck & Adams-Prassl, 2021; Sezen et al., 2023).

This paper introduces CRISight, a pre-launch Cannibalisation Risk Index. It integrates seven risk domains into one transparent decision framework and retains evidence confidence and strategic tolerance as separate advisory levels. CRISight does not seek to present an unvalidated cannibalisation percentage before launch. Instead, it estimates the conditions under which internal demand transfer is more likely to occur and guides redesign, positioning, pricing, channel and portfolio decisions before commercial commitment.

Problem Statement

Introducing new products and extending established brands remain important strategies for business growth. By using an existing brand name, firms may reduce the cost and uncertainty associated with introducing a completely new brand, while benefiting from the awareness, associations and customer base already developed by the parent brand. However, the success of a new product at the individual product level does not necessarily indicate growth at the overall brand or portfolio level. A new product may generate sales by attracting new category buyers or customers from competing brands, but it may also obtain a considerable portion of its sales from the firm's existing products (Van Heerde et al., 2010). This internal transfer of demand is generally known as product cannibalisation.

Cannibalisation is particularly relevant to line extensions because the new and existing products operate within the same category and may compete for similar customers, usage situations and purchase occasions. Evidence from 36,994 line extensions shows that many extensions do not perform better than the existing products in their categories, while their long-term survival rates remain uncertain (Victory et al., 2024). More recent research also indicates that similarity between a line extension and the parent brand can produce substitution effects within the brand portfolio (Sezen et al., 2023). Therefore, a new product may report strong sales while contributing limited incremental growth to the overall portfolio. The launch may also require advertising, production capacity, distribution support and retail space that could otherwise have been allocated to existing products (Sezen et al., 2023).

The difficulty is that the total sales of a new product do not show where its demand originates. Van Heerde et al. (2010) demonstrate that new-product demand may consist of several sources, including primary demand, switching from competitors and cannibalisation of the firm's own products. Their analysis also shows that cannibalisation can occur across product categories and that the contribution of each demand source may change over time. Consequently, evaluating a new product only through sales volume or market share may overstate its contribution to company growth (Sezen et al., 2023). A product can appear successful independently while producing only a small increase in total portfolio sales or profit.

Another concern is that cannibalisation cannot be explained adequately by one product characteristic or one measurement method. Lomax (1996) compared gains-loss analysis, duplication-of-purchase analysis and deviation from expected share movements. The findings showed that the methods produced different views of cannibalisation and that some of the line extensions examined cannibalised their parent brands to some extent. This suggests that cannibalisation is a multidimensional and dynamic problem rather than an outcome that can be represented reliably by a single similarity measure.

Recent evidence further shows that product similarity is an important but incomplete explanation. Sezen et al. (2023) found that greater feature similarity increased the cannibalising effect of line extensions across three

consumer packaged-goods categories. They also found that introducing the extension under a sub-brand did not necessarily protect the existing brand from cannibalisation. However, product and brand similarity alone cannot determine whether customers will switch. A new product must first enter the customer's consideration set before it can replace an existing choice. Abaluck and Adams-Prassl (2021) demonstrate that consumers do not necessarily consider every available alternative and that limited attention can be mistaken for loyalty or switching resistance. Thus, two products may be highly similar, but the cannibalisation effect may remain limited if the new product is not noticed, considered or available during the same purchase journey.

Cannibalisation risk is also influenced by factors beyond the physical product. For example, channel and geographic separation can reduce the extent to which a new offer competes with an existing product (Ngwe, 2017). Perceived value also involves a wider comparison of benefits and sacrifices rather than price alone. Based on a meta-analysis of 687 articles involving 357,247 customers, Blut et al. (2023) found that customer-perceived value is most appropriately represented by a combination of benefits, sacrifices and overall value. In addition, recent brand-extension research shows that perceived fit contains several dimensions, including physical, situational, targeting, pricing, complementary and conceptual fit (Biallowons et al., 2026). These findings indicate that cannibalisation risk may develop through multiple overlapping conditions involving customers, product benefits, value, usage situations, channels, brand architecture and switching behaviour.

Despite these risks, most established methods for measuring cannibalisation depend on information that becomes available only after a product has been launched. These methods commonly use sales records, market shares, consumer panels, household switching data or econometric demand models to estimate the demand transferred from existing products (Van Heerde et al., 2010; Lomax, 1996). Such approaches are valuable for explaining realised cannibalisation, but they offer limited support during the earlier stage when managers must decide whether the proposed product should be launched, redesigned, repositioned, repriced or distributed through different channels. Therefore, managers may recognise the cannibalisation problem only after substantial resources have already been committed.

Research Gap

The first research gap concerns the timing of existing cannibalisation measurements. Previous studies provide important methods for identifying and estimating cannibalisation after a product has entered the market. However, relatively less attention has been given to developing a structured and empirically testable framework that assesses cannibalisation risk before launch. Even recent line-extension studies mainly examine actual sales, penetration, repeat purchasing, survival or cannibalisation after market introduction (Sezen et al., 2023; Victory et al., 2024, 2025). These studies provide valuable benchmarks, but they do not offer a complete pre-launch index that managers can use before actual sales data exist.

The second gap is the fragmentation of cannibalisation-related factors across different areas of literature. Product and feature similarity is examined in line-extension research (Sezen et al., 2023), consumer attention and consideration are examined in choice research (Abaluck & Adams-Prassl, 2021), perceived value is studied within value literature (Blut et al., 2023), and channel separation is examined in retail research (Ngwe, 2017). Research on brand-extension fit also identifies several dimensions of fit, but it mainly focuses on extension evaluation and acceptance rather than predicting internal sales transfer (Biallowons et al., 2026). Although these studies explain important parts of the cannibalisation process, the factors have not been sufficiently integrated into one theory-driven pre-launch risk framework.

The third gap concerns the separation between customer overlap and actual switching. Existing customers may purchase both the proposed and existing products without fully replacing either product. Shared buyers or duplication of purchase may therefore indicate competitive proximity, but they do not automatically establish that cannibalisation has occurred. Similarly, high purchase intention towards a new product does not reveal whether the purchase would replace an existing internal product, replace a competitor's product or represent an additional purchase. A pre-launch assessment must therefore capture the counterfactual source of demand rather than depend only on general purchase intention, product attractiveness or customer overlap.

The fourth gap concerns the distinction between a cannibalisation risk score and a realised cannibalisation percentage. An index score represents the strength of conditions associated with possible internal demand transfer. However, a realised cannibalisation rate is the percentage of new-product sales transferred from the firm's existing products. A pre-launch risk score has no meaning as an equivalent cannibalisation percentage without post-launch outcomes for longitudinal calibration. This is a key difference, because labelling an uncalibrated score as a predicted percentage of sales lost would lend false precision and undermine the credibility of the framework.

The fifth gap is related to the strategic interpretation of cannibalisation. Internal demand transfer is not necessarily a bad thing. Cannibalisation may be acceptable if the new product has a better margin, replaces an obsolete offer, prevents customers going to competitors or is part of a planned portfolio migration. For example, Chandrasekaran et al. (2022) show that cannibalisation decisions in technological change must be considered together with the transition and survival strategy of the firm. In this way, the risk of cannibalisation can be distinguished from its acceptance by management. Including the two issues in the same score may unfairly lower the rating of an actual high-risk issue simply because the firm views the transfer as strategically acceptable.

CRISight is proposed to address these gaps by integrating seven pre-launch risk constructs: Customer-Segment Overlap, Internal Switching Propensity, Product and Benefit Similarity, Price and Perceived-Value Proximity, Usage-Occasion Overlap, Channel and Market-Access Overlap, and Brand and Portfolio Proximity. These constructs represent different but connected conditions through which a proposed product may displace demand from existing products. CRISight also separates the raw cannibalisation risk score from Evidence Confidence and Strategic Cannibalisation Tolerance. Accordingly, the framework is intended to provide a more transparent and diagnostic assessment of cannibalisation risk before launch, while its weights, thresholds and conversion into a potential cannibalisation percentage must be validated using historical and longitudinal post-launch data.

Research Questions and Conceptual Scope

The main objective is to develop a literature-grounded conceptual framework for estimating product cannibalisation risk before launch. Five specific objectives guide the paper: to trace the development of cannibalisation thinking, compare commonly used metrics, explain the behavioural and portfolio mechanisms behind internal switching, define seven measurable risk constructs, and propose a validation and calibration programme for CRISight.

The paper addresses five research questions:

- RQ1: How have the understanding and measurement of product cannibalisation developed over time?
- RQ2: What factors should be included in a pre-launch cannibalisation risk framework?
- RQ3: How should the seven proposed factors be combined and weighted to develop a reliable risk index?
- RQ4: How can the risk score be converted into an estimated cannibalisation percentage?
- RQ5: How should evidence quality and the company's willingness to accept cannibalisation be included without changing the actual risk score?

CRISight focuses on the risk that demand for a proposed product will be transferred from another product within a defined internal portfolio. The relevant boundary can be a parent SKU, product line, brand family or multi-brand company portfolio, but it must be declared before assessment. This is important because cross-category and sister-brand effects can otherwise be missed (Van Heerde et al., 2010).

The framework is intended for line extensions, brand extensions and closely related new offerings where consumers can realistically substitute between the proposed and existing products. It does not replace a full new-product forecast, profitability model or market-sizing study. Instead, it adds a disciplined portfolio lens to those analyses. The conceptual unit is a pair of a proposed product and an incumbent product. When several

incumbents exist, pairwise scores may be aggregated according to sales exposure, customer-base size or strategic importance, although the most appropriate aggregation method must be determined empirically.

LITERATURE REVIEW

Evolution of Cannibalisation Concern

The initial real concern was straightforward: when a company introduced an additional variant, some of its sales came from existing products. Mason and Milne (1994) put this concern into the framework of mature portfolios and highlighted customer transfer across products owned by the same company. Cannibalisation can be seen in different ways depending on the measurement methods (Lomax, 1996). The study compared gains–loss analysis, duplication of purchase and deviation from expected share movement and showed that cannibalisation is a dynamic rather than a static metric.

Demand-source decomposition was the next development. Kadiyali et al. (1998) linked line extensions with competitive interaction, and combined demand and contribution. Their work helped to move discussion away from the assumption that every internal transfer is automatically damaging. Van Heerde et al. (2004) decomposed promotional sales changes into cross-brand, cross-period and category-expansion effects. Van Heerde et al. (2010) then developed a dynamic model for pioneering innovations that separated internal cannibalisation, competitor switching and primary demand, including cross-category effects.

Recent literature gives more attention to the conditions producing cannibalisation. Sezen et al. (2023) show that feature similarity and brand architecture have distinct sales effects in line extensions. Victory et al. (2024) provide recent empirical benchmarks on line-extension performance and cannibalisation. Research on circular offerings also shows that awareness and consideration can materially change estimated cannibalisation (Koide et al., 2023).

Recent studies also broaden the decision context. Cho and Janda (2022), He, Mo, and Fu (2023), He, Mo, Wan, et al. (2023), and Pedrosa et al. (2024) show that extension direction and consumer beliefs affect responses to upward or downward extensions. Li et al. (2021) connect product design and online information, while Chandrasekaran et al. (2022) examine cannibalisation during disruptive technological change. Okorie et al. (2021) extend the issue to circular production and remanufacturing. These papers do not estimate the same rate but they validate that the internal transfer is determined by product, consumer, channel, technology and sustainability conditions.

The journey is therefore from observation, through measurement and causal decomposition, to prediction and decision support. The last step is CRISight. It translates existing ex-post knowledge into an ex-ante structure, while it can only become a predictive index once it has been validated with real launches.

Cannibalisation Definition and Metrics

A useful definition for CRISight is: demand that a proposed product gains from another product in the same defined firm portfolio. The definition involves three decisions. First, “demand” may refer to customers, units, revenue, margin, or probability of choice. Second, “at the expense of” is counterfactual: what would buyers have chosen had the proposed product not been offered? Thirdly, the internal portfolio boundary should be determined prior to analysis.

The simplest post-launch rate is internal sales transfer divided by total sales of the new product. However, the numerator should not equal every observed decline in an incumbent. Sales may fall because of competitors, stock-outs, seasonality, category decline, economic changes or the firm’s own marketing reductions. Strong estimation therefore uses matched controls, household switching, choice models, market-response models, or demand decomposition (Aguilar-Palacios et al., 2021).

Several methods have been used to measure product cannibalisation and substitution. Gains–loss analysis tracks customers or purchases that move from one product to another, while duplication-of-purchase analysis measures the extent to which two products share the same buyers (Lomax, 1996). Although shared buying can indicate that two products compete closely, it does not necessarily mean that one product has replaced the other. Deviation-from-expected-share analysis provides another perspective by comparing actual market-share changes with the movements normally expected within the market (Lomax, 1996). Diversion ratios estimate the proportion of customers who move to another product after a change in the price, quality or availability of their original choice (Conlon & Mortimer, 2021). For pre-launch assessment, conjoint analysis and discrete-choice experiments can estimate consumer preferences and possible product substitution by varying product attributes and presenting respondents with realistic choice alternatives (Eggers et al., 2021). After launch, econometric decomposition can use longitudinal market data to separate demand gained from the firm's existing products, competing products, and new category demand, while also considering how these effects change over time (Van Heerde et al., 2010).

Each metric answers a different question. No single method is universally best, consistent with the findings of Lomax (1996). CRISight should therefore be validated against several outcomes: realised internal transfer rate, incumbent sales change after controls, portfolio contribution, and the share of new-product demand taken from competitors or primary demand. This multi-criterion approach reduces the danger of optimising the index for one narrow definition.

CRISight Architecture and Theoretical Foundation

CRISight rests on three interrelated ideas, not a single, all-purpose theory. The first is demand source logic. Transfers among internal products, transfers from competitors, market expansion and timing changes create new-product demand (Van Heerde et al., 2004, 2010). This specifies the final outcome to be predicted by CRISight.

The second is consumer choice and thought. Managers cannot assume that a new product will cannibalise an existing one simply because they think the products are similar. The customer must know about the new product, place it in a relevant consideration set and prefer it sufficiently to change choice. Abaluck and Adams--Prassl (2021) show why consideration must be separated from preference. This logic directly supports Internal Switching Propensity and also explains why customer, occasion and channel overlap create opportunity as opposed to guaranty transfer.

Third, fit of categorisation and extension. Consumers evaluate the extension's attributes, benefits, and brand cues against what they know about the parent. Aaker and Keller (1990) have demonstrated perceived fit in brand-extension evaluation. Recent research has found that brand-extension fit is multidimensional and that functional similarity and brand-related fit should not be considered as one general judgement (Deng & Messinger, 2022).

These foundations yield a simple causal story. Overlap in customers, occasions and channels creates exposure to both products. Similarity in benefits, value and portfolio cues increases perceived substitutability. Consideration and switching determine whether potential substitution becomes internal transfer. Strategy then determines whether the transfer is harmful, acceptable or desired. The seven constructs represent the risk conditions; strategic tolerance represents managerial interpretation after risk has been estimated.

The CRISight architecture contains three linked outputs. Output 1 is the raw Cannibalisation Risk Index, formed by the seven constructs. Output 2 is Evidence Confidence, which reports how strongly the score is supported. Output 3 is Strategic Cannibalisation Tolerance, which evaluates whether internal transfer may be acceptable for portfolio reasons.

The seven constructs are modelled formatively. Customer overlap does not have to move together with price proximity, and channel overlap does not have to move together with usage occasion. A launch can therefore receive the same total risk score through different profiles. For managerial use, the seven-factor profile must always accompany the overall score so that action remains diagnostic.

The conceptual scoring form is $CRISight = \sum(w_j C_j)$, where C_j is the standardised construct score and w_j is its weight. During early pilot work, equal weights of $1/7$ are the most transparent baseline. PCA-derived or predictive weights may later be compared, but they should not be treated as universal. PCA identifies dimensions that explain variance in a particular data set; it does not automatically identify the factors that best predict future cannibalisation or profit.

Customer-Segment Overlap (CSO)

Customer-Segment Overlap is the extent to which the proposed product and existing internal products are likely to attract the same buyers. Internal transfer is impossible without some overlap in the people who can realistically choose both offers. However, overlap is an enabling condition, not direct proof of cannibalisation.

Mason and Milne (1994) provide the portfolio foundation because cannibalisation involves customer gains by one internal offer at the expense of another. Contemporary evidence on brand competition also warns that manager-defined segments are often less separated than positioning documents suggest (Sharp et al., 2024). Actual brand buyers commonly overlap, and repertoire purchasing means that consumers may buy several brands or variants over time. Victory et al. (2024) similarly show the value of using observed line-extension performance rather than relying only on managerial expectations.

CSO can be measured using shared target needs, demographic and behavioural profiles, current customer bases, purchase repertoires and basket overlap. Survey items should ask whether the same customers would seriously consider both products, not merely whether marketing descriptions use the same segment label. Behavioural data can add shared-customer ratios. The expected relationship is positive: greater customer overlap increases cannibalisation risk, while its effect should become stronger when switching propensity and product substitutability are also high (Koide et al., 2023). Sharp et al. (2024) review empirical regularities showing that competing brands commonly share buyers and that mental and physical availability are central to competition. This challenges the assumption that manager-defined target segments are neatly isolated. Ngwe (2017) adds a structural channel perspective: outlet locations can segment consumers through travel sensitivity and preference for newness, reducing cannibalisation of regular-store revenue. Together, these findings support separate Customer-Segment Overlap and Channel and Market-Access Overlap dimensions.

Proposition: Higher customer-segment overlap is associated with higher pre-launch internal cannibalisation risk, subject to the other CRISight conditions.

Internal Switching Propensity (ISP)

The Internal Switching Propensity is the likelihood that a customer who would otherwise choose an existing internal product will choose the proposed product. This is the behavioural mechanism most similar to cannibalisation, and should be distinguished from general purchase intention.

Non-choice can be a signal of inattention rather than strong preference or high switching costs (Abaluck and Adams-Prassl, 2021). This is important because if buyers do not see or think of a similar product, there may be little transfer. On the other hand, a well-publicized extension might quickly make its way into the incumbent's consideration set. Recent work on circular offerings also demonstrates that awareness and consideration can change anticipated levels of cannibalisation (Koide et al., 2023).

ISP should use counterfactual tasks. Respondents can allocate their next 10 purchases or 100 points among the incumbent, proposed product, competitor options, and no purchase. Direct questions can assess likelihood of replacement, willingness to move and whether purchases would be additional. Choice experiments should include realistic competitors and a no-purchase option. The expected relationship is positive. ISP may also mediate the influence of similarity and overlap because those conditions increase risk mainly when they translate into actual internal choice displacement.

Proposition: Higher internal switching propensity is associated with higher pre-launch internal cannibalisation risk, subject to the other CRISight conditions.

Product and Benefit Similarity (PBS)

Product and Benefit Similarity is the extent to which the proposed and incumbent products share features, functions, performance, ingredients, format and promised benefits. It captures functional substitutability rather than visual or naming similarity.

Sezen et al. (2023) provide direct recent evidence from three consumer packaged-goods categories. They separate feature similarity from brand-name similarity and find that minimising feature similarity is more important for limiting cannibalisation and improving incremental sales. Their findings also show that using a sub-brand does not automatically protect the parent when the offers remain functionally close. Product-line research further indicates that weak differentiation can intensify internal competition. Drawing on 2,134 effect sizes, Peng et al. (2023) demonstrate that extension fit is an important determinant of brand-extension success. Together with the multidimensional fit framework proposed by Deng and Messinger (2022), this supports the separation of Product and Benefit Similarity from Brand and Portfolio Proximity rather than collapsing both into a generic similarity score.

PBS items should compare core function, benefit, problem solved, performance, format and expected outcome. Expert coding can complement customer perceptions because technical similarity and perceived similarity may differ. The proposed relationship is positive: higher product and benefit similarity increases the probability that customers treat the new offer as a replacement. Managers can reduce PBS risk through a distinctive benefit, format, use case, technology or performance level, but cosmetic changes alone should not be treated as meaningful differentiation.

Proposition: Higher product and benefit similarity is associated with higher pre-launch internal cannibalisation risk, subject to the other CRISight conditions.

Price and Perceived-Value Proximity (PVP)

Price and Perceived-Value Proximity refers to closeness in the total value propositions of the proposed and incumbent products. It includes monetary price, benefits, quality, effort, time, risk and other sacrifices. Two products with different prices may still be close in perceived value.

Blut et al. (2023) synthesise 687 articles, 780 samples and 357,247 customers. Their meta-analysis supports an integrative view in which perceived value combines benefits, sacrifices and overall evaluation. This evidence means that a simple price-gap indicator is too narrow. Recent vertical-extension research also treats price and quality movement together because an upward or downward extension changes the reference point and can alter parent-brand evaluation (Schmitz et al., 2023).

PVP should compare net value, willingness to pay, quality for price, non-monetary sacrifices, promotion-adjusted prices, and expected ownership or usage costs. Reverse coding may be needed because a small difference means greater proximity and higher risk. The expected relationship is positive when customers see the two products as offering similar value for similar sacrifice. Managers may reduce risk by creating a clear value ladder, but an artificial price gap without benefit differentiation may only shift perceptions temporarily.

Proposition: Higher price and perceived-value proximity is associated with higher pre-launch internal cannibalisation risk, subject to the other CRISight conditions.

Usage-Occasion Overlap (UOO)

Usage-Occasion Overlap is the extent to which the proposed and incumbent products are bought and used for the same purpose, time, place, frequency, social setting, and consumption routine. It recognises that similarity at product level does not always mean substitution in practice.

Cheng et al. (2024) show across five studies that rare and frequent consumption occasions change consumers' reliance on feelings and reasons. Their work is not a direct cannibalisation study, but it provides recent evidence that occasion characteristics influence choice processes. Occasion-based segmentation is therefore useful when assessing whether two similar products compete or complement one another.

UOO items should assess purpose, timing, frequency, location, user situation, and complementarity. Researchers can use usage diaries, jobs-to-be-done interviews or scenario-based choice tasks. The proposed relationship is positive: greater overlap in usage occasion increases cannibalisation risk. However, complementary use should reduce risk even when features and brand cues are similar. Managers can create separation by assigning the extension a distinct routine, time, context or consumption goal and communicating that role consistently.

Proposition: Higher usage-occasion overlap is associated with higher pre-launch internal cannibalisation risk, subject to the other CRISight conditions.

Channel and Market-Access Overlap (CMA)

Channel and Market-Access Overlap is the degree to which customers encounter and can purchase the proposed and incumbent products in the same physical, digital and geographic markets. It captures the opportunity for substitution created by availability.

Ngwe (2017) demonstrates that outlet location and customer travel sensitivity can segment demand and reduce cannibalisation of regular-store revenue. This provides strong evidence that channel and geography are not only execution details; they can be deliberate portfolio controls. Omnichannel expansion makes the issue more complex because products may be separated physically but compared instantly online.

The CMA should assess distribution channels, search and recommendation environments, shelf or webpage proximity, geographic markets, delivery reach and availability timing. Digital visibility deserves special attention because algorithmic recommendations can place two internal products beside each other even when managers intended separate segments. The expected relationship is positive: greater access overlap makes internal switching easier. Possible mitigation includes selective channels, phased geography, differentiated retail partners, exclusive formats or separated launch timing, provided these choices do not destroy total reach.

Proposition: Higher channel and market-access overlap is associated with higher pre-launch internal cannibalisation risk, subject to the other CRISight conditions.

Brand and Portfolio Proximity (BPP)

Brand and portfolio proximity is the extent to which consumers view the proposed and incumbent products as closely related members of the same brand system and perceive similar portfolio roles. This includes name, endorsement, visual identity, extension cues and strategic positioning.

Sezen et al. (2023) show the independent effects of brand architecture and feature similarity and that sub-branding does not necessarily reduce cannibalisation. Furthermore, research on brand-extension fit supports the differentiation of multiple dimensions of fit, rather than a single general similarity judgement (Deng & Messinger, 2022). This implies that functional and portfolio proximity should be measured separately.

BPP items should contain shared master brand, naming structure, visual assets, packaging codes, endorsement, perceived family membership, role clarity, complementarity and duplication. A highly cohesive portfolio can help with recognition, but maximum similarity is not always desirable if the extension needs a distinct role. A positive relation is expected when close portfolio cues make customers perceive the new product as a direct substitute. Managers can influence BPP through architecture, descriptor, design and role clarity, but such decisions should be consistent with long-term brand equity.

Proposition: Higher brand and portfolio proximity is associated with higher pre-launch internal cannibalisation risk, subject to the other CRISight conditions.

The CRISight Framework and Propositions

CRISight is proposed as a formative higher-order risk index. The dimensions are distinct risk sources; they are not interchangeable reflections of one psychological state. Removing a dimension changes the meaning of the index. The core architecture contains seven dimensions. Evidence Confidence (ECC) and Strategic Cannibalisation Tolerance (SCT) sit outside the core risk score.

Code	Dimension	Operational meaning	Main literature foundation
CSO	Customer-Segment Overlap	Extent to which proposed and incumbent products appeal to the same real customer base, needs, and buyer profiles.	Mason & Milne, 1994; Sharp et al., 2024
ISP	Internal Switching Propensity	Likelihood that buyers replace, reduce, postpone, or migrate purchases from the incumbent to the proposed product.	Abaluck & Adams-Prassl, 2021; Van Heerde et al., 2010
PBS	Product & Benefit Similarity	Similarity in functions, features, benefits, quality, design/format, and problem solved.	Sezen et al., 2023; Lomax, 1996; Deng & Messinger, 2022
PVP	Price & Perceived-Value Proximity	Closeness of price tier and total benefits-versus-sacrifices value proposition.	Blut et al., 2023; Lomax, 1996
UOO	Usage-Occasion Overlap	Extent to which products serve the same purpose, timing, routine, place, and consumption occasion.	Cheng et al., 2024; Lomax, 1996; Deng & Messinger, 2022
CMA	Channel & Market-Access Overlap	Extent to which products are encountered and purchased through the same channels, locations, and purchase journeys.	Ngwe, 2017; Sharp et al., 2024
BPP	Brand & Portfolio Proximity	Perceived closeness through naming, brand architecture, visual assets, packaging, and portfolio position.	Sezen et al., 2023; Deng & Messinger, 2022; Biallowons et al., 2026

Table 1: CRISight Framework and Propositions

The seven constructs are not to be read as seven independent causes with identical effects across each category. Their combinations are probably important. Customer overlap provides a pool of potential switchers, while channel overlap determines whether those people will encounter both products. Product similarity, value similarity and brand similarity influence perceived substitutability. The usage occasion defines the relevance of replacement and the switching propensity captures the final behavioural movement.

Some of these interactions are of theoretical importance. PBS may be more effective when UOO is high, as similar products for the same purpose are easier substitutes. PVP may improve switch performance when customers see little net value difference. CMA may strengthen CSO because customers with overlaps cannot easily switch if the proposed product is not available on their market. BPP can raise awareness and consideration, but its effect may be less powerful than functional similarity, consistent with Sezen et al. (2023)'s results. These interactions imply that a simple additive index is a good first approximation but not necessarily the ultimate predictive model. Empirical validation should compare four models: equal-weight additive, PCA-weighted, supervised predictive, and models with selected interactions. Model selection should be guided by out-of-sample accuracy, calibration and interpretability rather than the in-sample fit alone.

The framework also suggests possible threshold effects. Even when products are similar, risk can be limited by low overlap in customers or occasions of use. Alternatively, very high switching propensity may dominate a number of moderate antecedents. Such possibilities should be tried and not assumed. Thus, CRISight should provide factor profiles and not conceal all information in a single aggregate score.

During development, a number of candidate indicators should be used to measure each core dimension. Consumer facing constructs can be measured using five point agreement or similarity scales. Add objective indicators where data is available. The initial pool of items for the development should be intentionally broader than the final instrument, as item reduction needs to be evidence-based. The final short form should be selected only after content, construct, and predictive validity.

Dimension	Example of candidate metrics
CSO	Segment overlap coefficient; share of proposed-product intenders who currently buy the incumbent; needs-cluster overlap
ISP	Forced-choice switching probability; reduction in intended incumbent purchase frequency; share-allocation transfer from incumbent
PBS	Perceptual similarity; weighted feature overlap; benefit-map distance; number of unique versus shared benefits
PVP	Relative price gap; same-tier indicator; perceived value similarity; benefits-sacrifices comparison
UOO	Overlap in purpose, daypart, location, purchase mission, routine and social setting
CMA	Retail/platform overlap; shelf or screen adjacency; search co-appearance; geographic coverage overlap
BPP	Name similarity; shared distinctive assets; package/visual similarity; sub-brand/endorsement structure; portfolio position

Table 2: Dimension Scoring

Evidence Confidence

Evidence Confidence indicates how much trust managers should place in the risk estimate (Ward et al., 2024). It is not an eighth risk construct and should not mathematically reduce a high score. A high-risk, low-confidence case means that risk appears high, but the supporting evidence is weak. Calling the case moderate would hide uncertainty and may encourage an unsafe launch.

Confidence indicators can include the use of actual category customers, representative sampling, sufficient sample size, realistic prototypes, inclusion of current incumbent users, objective product and price information, competitor and no-purchase options, behavioural choice data, historical analogues, cross-functional review and consistency across evidence sources. Recency also matters in trend-sensitive categories.

Confidence can be reported as Low, Moderate or High, supported by an audit trail. Low confidence should trigger stronger research, not automatic rejection. Moderate confidence may be sufficient for an inexpensive pilot. High confidence is needed when the launch involves major capital, irreversible brand architecture or extensive distribution commitments.

Keeping confidence separate supports good governance. Decision makers can distinguish “the risk is low” from “we do not know the risk.” This separation also helps later validation because errors can be analysed according to the quality of pre-launch evidence.

Strategic Cannibalisation Tolerance

Strategic Cannibalisation Tolerance is a matter of internal transfer being acceptable or desirable. It is to be considered after raw risk because the willingness to accept a consequence does not change its likelihood. Kadiyali et al. (1998) found that line extension can influence pricing and competition and improve the combined contribution. Studies on product-rollover also suggest that cannibalisation, postponement and profit can be interrelated in launch decisions (Chen et al., 2024).

The new offer may have a better margin, may protect customers from competitor movement, support planned migration, replace an obsolete product, reduce cost, reach a strategic segment or strengthen the future portfolio. Tolerance may be high. Tolerance may be low if the incumbent is highly profitable, strategically important, capacity constrained or protected by channel commitments.

The aggregated decision logic is feasible. Usually low risk is a reason to go. Weak evidence, moderate risk needs more research. Moderate or high risk low tolerance requires redesign, repositioning, repricing or channel separation. High risk/high tolerance may justify a controlled migration. But, performance should be measured at the total portfolio level, not by celebrating new-SKU sales.

This module converts CRISight from a warning score to decision support without losing measurement integrity. It also avoids the common mistake of treating zero cannibalisation as the optimal goal. Sometimes a competitor does not cannibalise the incumbent (Dell'Era et al., 2020).

Index Formation, Weighting and Dashboard Interpretation

Each CRISight construct can initially be measured using four to six items on a five- or seven-point scale. Negatively worded items should be used carefully because they can produce method effects (Elek et al., 2025). After item aggregation, the seven construct scores should be transformed to a common 0–100 scale so that they can be compared and combined within the index. Composite indices require an appropriate method for determining the relative contribution of their constituent dimensions. Principal Component Analysis (PCA) is a widely used data-reduction procedure that transforms a set of correlated variables into uncorrelated principal components representing the common information contained in the data (Abdi & Williams, 2010). The first principal component accounts for the largest proportion of the total variance, and its coefficients can be used to derive data-adaptive weights for a composite index. Filmer and Pritchett (2001), for example, applied PCA to determine the relative weights of variables when constructing an asset index.

In CRISight, PCA may be applied to the seven dimension scores during exploratory pilot testing. The coefficients obtained from the first principal component indicate the relative contribution of each dimension to the common covariance structure of the pilot dataset. After all dimensions have been directionally aligned, the coefficients can be normalised so that the resulting weights sum to one. The overall Cannibalisation Risk Index is therefore expressed as:

$$CRI_i = \sum_{j=1}^7 w_j C_{ij}, \quad \sum_{j=1}^7 w_j = 1$$

where CRI_i is the total pre-launch cannibalisation risk score for proposed offering i , C_{ij} is the normalised score of offering i on CRISight dimension j , and w_j is the weight assigned to dimension j .

In the earlier development of CRISight prototype dashboard, the following provisional illustrative weights were used:

$$CRI = 0.1930(CSO) + 0.1017(ISP) + 0.1900(PBS) + 0.1504(PVP) + 0.1370(UOO) + 0.0790(CMA) + 0.1488(BPP)$$

where CSO represents Customer-Segment Overlap, ISP represents Internal Switching Propensity, PBS represents Product and Benefit Similarity, PVP represents Price and Perceived-Value Proximity, UOO represents Usage-Occasion Overlap, CMA represents Channel and Market-Access Overlap, and BPP represents Brand and Portfolio Proximity. The reported coefficients sum to approximately one, with the minor difference arising from rounding. Because each dimension is scored on a common 0–100 scale, the weighted CRI also ranges approximately from 0 to 100.

These coefficients should be interpreted as provisional pilot weights rather than universal CRISight weights. At the conceptual and early pilot stages, equal weights of 1/7 provide the most transparent benchmark. Although PCA-derived weights may capture the covariance structure of a particular dataset, PCA maximises explained variance rather than prediction of realised cannibalisation or portfolio profit (Huang et al., 2021). Therefore, the performance of provisional PCA weights should be compared to equal weights and supervised predictive models across samples, product categories and market conditions. We should only estimate predictive weights from historical launches when the outcome is well defined. Regularised regression, PLS-based prediction, Bayesian models or gradient boosting may be considered, but the final method should provide a trade-off between accuracy, stability and explanation. Category-specific weights are acceptable if cross-validation shows better performance and minimum sample requirements are satisfied.

The dashboard should report on the overall risk score, risk band, seven factor ranking, evidence confidence and strategic tolerance. Show only a separate potential cannibalisation percentage if there is a calibrated mapping. The average similarity is not the same as the overall CRISight as it only relates to the similarity input, while the index includes customers, switching, value, occasion, channel and portfolio conditions.

Proposed Measurement Development

Measurement development should begin with qualitative domain specification. Interviews with brand managers, innovation teams, retailers and customers can test whether the seven domains are understandable and complete. Critical-incident interviews should examine real launches that created incremental growth, harmful cannibalisation or intentional migration.

Next, an expert panel should assess item relevance, clarity and construct placement. Content validity ratios and a modified Delphi process can be used (Ang et al., 2024). Cognitive interviews should then test whether respondents understand counterfactual questions such as “Would this purchase replace the existing product?”

A pilot survey should examine missing data, response patterns, item distributions and multicollinearity. Because the constructs are formative at the higher-order level, internal consistency alone is not sufficient. Reflective subscales, if used, require reliability and convergent/discriminant validity checks (Sharma et al., 2021). Formative indicators require content coverage, collinearity checks and significance or relevance of weights.

Measurement invariance should be examined across product categories and important customer groups before comparisons are made (Hair et al., 2024). The instrument should also be tested for common-method bias by combining customer responses with expert coding, product data and behavioural choice tasks (Ashraf et al., 2021). A short commercial form can be developed only after the full form shows stable predictive performance.

Predictive Validation and Rate Calibration

CRISight becomes a genuine predictive index only when pre-launch scores are linked to later outcomes. A longitudinal design should score multiple proposed launches before release and then track new-product sales, incumbent sales, competitor movement, total category demand and portfolio margin after launch.

The preferred target is a defensibly estimated internal transfer rate. Difference-in-differences, matched markets, household panels, switching data or structural demand models can help construct the counterfactual. The validation data set should include launches with different outcomes, not only successful products.

Performance should be assessed out of sample. Relevant indicators include mean absolute error for a predicted rate, Brier score and calibration slope for risk categories, rank correlation, sensitivity to harmful high-risk launches and incremental accuracy over simpler benchmarks such as product similarity alone (Johnston et al., 2025). Model stability across time and category is equally important.

Calibration can map a 0–100 risk score to an expected rate using logistic, beta or isotonic regression (Johnston et al., 2025). Prediction intervals should be displayed because point estimates can create false certainty.

Recalibration should occur when category behaviour, channels or competitive structure change. Historical data support pre-launch prediction because they train relationships using earlier launches; the focal product itself is still assessed before its sales occur.

Theoretical and Managerial Contribution

The first theoretical contribution is integration. CRISight links demand-source decomposition to consumer consideration, extension fit, perceived value, usage occasion, channel access and portfolio architecture. It thus explains cannibalisation as a choice-displacement process of multiple conditions rather than a similarity problem.

The second is construct separation. Functional similarity is distinguished from brand proximity, customer overlap from switching, price from total value, and raw risk from strategic tolerance. These distinctions decrease conceptual contamination and render the model more testable.

The third contribution is temporal in nature. Realised cannibalisation is often diagnosed using existing strong metrics. Those outcomes suggest a bridge to pre-launch assessment. CRISight explicitly says that validation is still needed. The fourth contribution is methodological: the paper offers a step-by-step route from transparent equal weighting to category-sensitive predictive calibration.

The framework provides managers with a structured launch discussion. High PBS score suggests differentiation of benefits High PVP suggests clearer value ladder High UOO suggests distinct usage role High CMA suggests channel/geography separation High BPP suggests architecture/role clarification High ISP suggests careful migration and portfolio forecast The output is therefore diagnostic, but not purely numerical.

Limitations and Directions for Future Research

CRISight is a conceptual framework and does not yet have universal weights, thresholds or predictive accuracy. The seven constructs are derived from the related literature, some of the evidence is indirect. Usage-occasion and perceived-value studies explain choice processes rather than realised rates of cannibalisation. These connections need to be tested empirically.

The differences among categories may be large. Fast moving consumer goods, services, durable goods, digital subscriptions and pharmaceuticals have different purchase frequencies, switching costs and portfolio structures. Future research should examine measurement invariance and calibration by category.

The endogeneity of the index could also be an issue. Managers decide together product features, prices and channels. Historical launches are not random. Estimating predictive weights calls for careful controls and causal inference. Organisational incentives can bias launch teams scoring their own product. Independent customer evidence and documented assumptions can reduce this risk.

Future research should include comparison of stated-choice and actual-choice data, tests of interaction and threshold effects, cross-category cannibalisation and measurement of profit consequences. It should also look at whether the benefits of using adaptive weights are worth the loss of simplicity. Finally researchers should test whether the framework predicts competitor capture and primary demand as well as internal transfer.

CONCLUSION

CRISight addresses a real weakness in new-product and brand-extension decisions. Growth is what firms need, but sales of a new offer do not necessarily translate into incremental profit. The critical issue is: where will the demand come from, and is the internal transfer harmful, acceptable or intentional?

Our proposed framework combines seven risk domains: Customer-Segment Overlap, Internal Switching Propensity, Product and Benefit Similarity, Price and Perceived-Value Proximity, Usage-Occasion Overlap,

Channel and Market-Access Overlap, and Brand and Portfolio Proximity. These constructs are conceptualised to account for different aspects of the process from exposure and substitutability to actual internal switching.

CRISight should be described with caution. It is a pilot index and theory-driven pre-launch risk framework for validation. The observed is not a cannibalisation rate. “Evidence Confidence” and “Strategic Cannibalisation Tolerance” should be separated. Initial equal or PCA weights are tentative. Final weights and risk-to-rate mappings are subject to out-of-sample validation against actual post-launch demand-source outcomes.

The end score is not the primary usefulness of CRISight. Its factor profile shows how a launch creates portfolio risk and what managerial lever may reduce that risk. CRISight can be developed from a conceptual framework to a credible pre-launch decision support index through systematic scale development, choice testing, longitudinal validation and category calibration.

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Appendix A: Illustrative Initial Item Pool

The following items are an initial development pool derived from the framework. They are not a validated final scale. The purpose of publishing a broad pool at this stage is to make the operational domain transparent before expert review, cognitive testing, and empirical purification.

Customer Segment Overlap (CSO)

Code	Candidate Item
CSO1	The proposed product is intended for the same main customer group as the existing product.
CSO2	Customers who currently buy the existing product are likely to be the main buyers of the proposed product.
CSO3	The two products appeal to customers with similar needs.
CSO4	The two products appeal to customers seeking similar benefits.
CSO5	The proposed and existing products have substantially overlapping customer profiles.

Internal Switching Propensity (ISP)

Code	Candidate Item
ISP1	I would choose the proposed product instead of the existing product.
ISP2	If the proposed product were available, I would buy the existing product less frequently.
ISP3	I would replace at least some purchases of the existing product with the proposed product.
ISP4	I would postpone buying the existing product while waiting for the proposed product.
ISP5	The proposed product would reduce my need for the existing product.

Product and Benefit Similarity (PBS)

Code	Candidate Item
PBS1	The two products provide similar core functions.
PBS2	The two products solve the same customer problem.
PBS3	The most important features of the two products are similar.
PBS4	The two products deliver comparable functional benefits.
PBS5	The proposed product does not provide a clearly distinct reason for purchase.

Price and Perceived-Value Proximity (PVP)

Code	Candidate Item
PVP1	The proposed and existing products are likely to fall within the same acceptable price range.
PVP2	Customers could choose between the products without substantially changing their budgets.
PVP3	The two products are likely to compete within the same price tier.
PVP4	The proposed product offers a price-value combination close to the existing product.
PVP5	The expected price of the proposed product makes it a realistic substitute for the existing product.

Usage-Occasion Overlap (UOO)

Code	Candidate Item
UOO1	The two products would normally be used in the same situation.
UOO2	The two products satisfy the same consumption goal.
UOO3	The proposed product would be used on occasions currently served by the existing product.
UOO4	The proposed product could replace the existing product in consumers' normal routines.
UOO5	Customers are unlikely to use the two products in complementary ways.

Channel and Market-Access Overlap (CMA)

Code	Candidate Item
CMA1	The proposed and existing products will be sold through the same main channels.
CMA2	Customers will encounter both products during the same purchase journey.
CMA3	The two products are likely to appear next to each other physically or digitally.
CMA4	The proposed product will be available in the same geographic markets as the existing product.
CMA5	Distribution overlap will make internal substitution easy.

Brand and Portfolio Proximity (BPP)

Code	Candidate Item
BPP1	The proposed and existing products will use highly similar brand names.
BPP2	Consumers will immediately recognise that both products belong to the same product family.
BPP3	The products will share similar logos or visual identity.
BPP4	The proposed product will be presented as a direct extension of the existing product.
BPP5	The proposed and existing products will occupy similar positions within the brand portfolio.

APPENDIX B: ILLUSTRATIVE DECISION LOGIC

Risk	Evidence Confidence	Strategic tolerance	Indicative action
Low	Any	Any	Proceed subject to normal launch evaluation.
Moderate	Low	Any	Collect stronger evidence before final decision.
Moderate	High	Low	Modify positioning, price, benefits, occasion, or channel.
Moderate	High	High	Controlled launch with migration monitoring.
High	Low	Any	Do not rely on score alone; conduct stronger choice or test-market research.
High	High	Low	Redesign, delay or reject the launch.
High	High	High	Proceed only as an intentional migration or defensive portfolio strategy, with monitoring.

These bands are illustrative only. Empirical thresholds should be established based on validated category data and decision consequences.