Retail atmospherics effect on store performance and personalised shopper behaviour: A cognitive computing approach

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Abstract

Purpose: The best possible way for brick-and-mortar retailers to maximise engagement with personalised shoppers is capitalising on intelligent insights. The retailer operates differently with diversified items and services, but influencing retail atmospheric on personalised shoppers, the perception remains the same across industries. Retail atmospherics stimuli such as design, smell and others create behavioural modifications. The purpose of this study is to explore the atmospheric effects on brick-and-mortar store performance and personalised shopper's behaviour using cognitive computing based in-store analytics in the context of emerging market.

Design/methodology/approach: The data are collected from 35 shoppers of a brick-and-mortar retailer through questionnaire survey and analysed using quantitative method.

Findings: The result of the analysis reveals month-on-month growth in footfall count (46%), conversation rate (21%), units per transaction (27%), average order value (23%), dwell time (11%), purchase intention (29%), emotional experience (40%) and a month-on-month decline in remorse (20%). The retailers need to focus on three control gates of shopper behaviour: entry, browsing and exit. Attention should be paid to the cognitive computing solution to judge the influence of retail atmospherics on store performance and behaviour of personalised shoppers. Retail atmospherics create the right experience for individual shoppers and forceful use of it has an adverse impact.

Originality/value: The paper focuses on strategic decisions of retailers, the tactical value of personalised shoppers and empirically identifies the retail atmospherics effect on brick-and-mortar store performance and personalised shopper behaviour.

Keywords: Retail atmospherics; In-store analytics; Cognitive computing; Shopper behaviour; Personalisation, Emerging market

Article classification: Research paper

1. Introduction

Shopping behaviour attempts to evaluate shopper impacts from organizations like family, friends, reference groups and society in particular (Foret and Procházka, 2007). The heterogeneity among individuals makes it a difficult task for brick-and-mortar retailers to understand shopper behaviour and therefore such retailers felt the need to acquire an in-depth understanding of the purchasing behaviour of shoppers. Shoppers have plenty of brick-and-mortar shops accessible to buy their required items (Enders and Jelassi, 2000) and the choice of a particular brick-and-mortar store has a direct impact on the behaviour of shoppers (Koo and Kim, 2013). Notable emerging market includes India (Gupta, 2013). Customer behaviour is positively influenced by conspicuousness, status consumption, brand name consciousness, need for uniqueness and hedonism in India, which in turn influences consumer purchase intention (Shahid *et al.*, 2021). Customer satisfaction and service quality are the best predictors of behavioural intentions in emerging economies (Hossain *et al.*, 2021). Shopper's affection for personal touchpoints and an imperative time-bound approach is required to deliver personalised information, matching to the shopper's individual needs instead of overwhelming them with a voluminous amount of comprehensive information (Behera *et al.*, 2020).

Retail atmospherics is the method of manipulating physical environment elements to influence shopper behaviour and generally includes music, sights and other stimuli of atmospherics (Turley and Milliman, 2000). Examples of shopper responses due to changes in atmospheric factors include enhanced sales and owing to the effect of various music styles and tempos (Petruzzellis *et al.*, 2018; Kulkarni, 2012; Morrison *et al.*, 2011), lighting (Biswas *et al.*, 2017), store layout (Wu *et al.*, 2014; Singh *et al.*, 2014), smells (Lunardo and Mbengue, 2013). By reducing cost, time, effort in maintaining or attracting new customers and evaluating individual consumers' perceptions of atmospheric factors can shape retail store image, raise customer value, raise performance and patronage intention (Kumar *et al.*, 2010). Therefore, it can concluded that shopper personalisation play a role in the atmospheric effect on store performance and shopper behaviour.

Retail atmospherics is an important element, as its importance is highlighted in literature. Atmospherics is a significant aspect of visitor experiences (Shao *et al.*, 2019). If a store is in an unpleasant atmosphere, shoppers will be hesitant to visit the mall, reducing their purchasing intention (El Hedhli *et al.*, 2013). The museum atmosphere affects brand trust, perceived quality, visitor satisfaction, and visitor behavioural intentions (Piancatelli *et al.*, 2020). Concerning the importance, the attention for further research is highlighted by different literatures. Situational and marketing factors define a new trend of shopping, but personal factors contributing to a positive and significant effect on the number of visits need further exploration (Hannah and Musyoka, 2019). Concerning personalisation, research should move its emphasis to include psychological factors such as emotions (Salonen and Karjaluoto, 2016). Personalisation is still a hazy, ill-defined term with no definite boundaries (Kwon and Kim, 2012) and is largely due to highly fragmentation in literature and lack of a strong theoretical foundation (Boerman *et al.*, 2017).

The development of new technology such as cognitive computing for data management and analytics allows brick-and-mortar retailers to leverage data in their business processes. Notable technologies like machine learning (ML), natural language processing (NLP), big data, Internet of Things (IoT), and cloud computing enable cognitive systems (Gudivada, 2016). Analytics services of the cognitive system are descriptive, diagnostics, predictive, prescriptive and cognitive analytics (Behera *et al.*, 2019). In-store analytics is the method of evaluating and drawing meaningful insights from the behavioural data on the in-store shopper and transaction data of brick-and-mortar retailers. Benefits offered by such analytics are the complete mapping of shopper journeys and improved relations, real-time insights on in-store footfall, effective shopper segmentation, campaign planning and integration with social media. IoT plays a critical role in producing real-time data for customer insights, which is critical for the organization's long-term survival (Yerpude and Singhal, 2019). Inflation rates in emerging economies are forecasted using shrinkage methods of ML algorithms (Özgür and Akkoç, 2021).

The existing research in retail atmospherics focuses primarily on shopper responses to environments (Roggeveen *et al.*, 2020, Toldos *et al.*, 2019, Pizzi *et al.*, 2019), while the strategic decisions of retailers and the tactical value of personalised shoppers have been mainly ignored. A strategic decision crystallises the present avenues for a retailer on how best to capitalise it by making the actionable time-bound decision, adopting sustainable practices and offering a memorable in-store experience. A tactical value involves looking at the retail sales data for each shopper individually and then tailoring the approach towards the characteristics of such individual shoppers. In India, physical storefronts are proving to be valuable to online retailers, who are extending their physical footprint, therefore measuring store performance is imperative. Consumers seek for the shopping experience in a physical store (Enders and Jelassi, 2000) and the outcomes of a shopping trip are influenced by shopper's behaviour (Schnack *et al.*, 2021), therefore measuring shopper behaviour is imperative. Operating more sustainably is a win-win opportunity for brick-and-mortar store, shopper with atmospherics as the environment. We could not find studies that empirically identify the linkage of retail atmospherics effect on brick-and-mortar store performance and personalised shopper behaviour.

The study aims to address this gap. Therefore, it has attempted to address the research questions (RQ) using cognitive computing based in-store analytics i.e., **RQ1:** how does retail atmospherics influence store performance? **RQ2:** how does retail atmospherics influence personalised shopper behaviour? To seek answer for RQs, this study proposes three-fold research objectives to measure the atmospheric effect on (i) brick-and-mortar store performance in the form of footfall count, conversation rate, units per transaction (UPT), and average order value (AOV), (ii) personalised shopper behaviour in the form of dwell time, emotional experience, purchase intention, and remorse. (iii) Formulation of shopper personalisation. In the context of this paper, a shopper is a customer who shops in the brick-and-mortar shop.

The remaining sections of the paper are structured as follows: The literature review are presented in Section 2, theoretical background, and the hypotheses are articulated in Section 3, the research method is outlined in Section 4, results are discussed in Section 5, the discussion is presented in Section 6 and the study is concluded in Section 7.

2. Literature Review

In order to meet the objective of this study, the literature review has presented with four themes and each theme is discussed below.

2.1. Influence of retail atmospherics on shopping behaviour

Neither retail atmospherics nor buying-related habits directly impact the re-patronage intention of the customer (Lim, 2020). Attention is a crucial precedent for interest, desire, and behavioural responses (search, action, and sharing) caused by the digital retail atmosphere, and for sports retail stores, positive results are more pronounced than luxury retail stores (Kim *et al.*, 2020). Atmospheric stimuli such as colour, music, and lighting have a significant impact on festival shopping engagement in India (Chatterjee and Shukla, 2020). Shoppers in a non-English speaking country are more likely to make purchases when they play music in English that fits the global image of the store (Toldos *et al.*, 2019). Shopping outcomes due to the atmospheric effects of music and scent yield higher satisfaction (Roschk *et al.*, 2017).

2.2. Role of personalisation on shopper satisfaction

Personalisation has a major effect on shopper satisfaction, service assessment and is the most critical determinant of perceived service efficiency, customer loyalty and other patronage indicators (Mittal and Lassar, 1996). Personalisation is both an intrinsic and extrinsic motivator for shopper satisfaction (San-Martín and Jimenez, 2017). Personalised messages delivered via a voice agent are effective at instilling positive attitudes about a product (Rhee and Choi, 2020). Personalisation of advertising messages has been the powerful determinant of developing positive attitudes toward the product and brand (Kang *et al.*, 2016; Ho and Bodoff, 2014).

2.3. Role of shopper personalisation on store performance

Personalisation has become more relevant in the omnichannel context since the convergence of channels has great potential in providing a more personalised customer experience (Hänninen *et al.*, 2019) and customer experience drives business growth (Keiningham *et al.*, 2020). Shopper personalisation has a positive impact on business outcomes (Thürmel *et al.*, 2021). Personalisation provides customers with advantages such as convenience, efficiency and individualisation that result in the increasing intention to buy from a store that uses it (Lee and Cranage, 2011). The number of personalised communications sent by businesses is on the rise (Yerpude and Singhal, 2019).

2.4. Retail atmospherics stimuli

Cleanliness has an impact on shopper's revisit intentions (Barber *et al.*, 2011). Music played in a store can have a major effect on a number of behaviour including sales, excitement, perceptions of and real time spent in the environment, traffic flow and visual stimulation perception in the retail store (Turley and Milliman, 2000). The scent affects sales, processing time, behaviour-seeking variety and perceived time spent in a store (Turley and Milliman, 2000). Shoppers do not walk without feeling the ambient temperature while entering a store (Ballantine *et al.*, 2015). Lighting factors can affect store image as well as merchandise inspection and handling (Turley and Milliman, 2000). The colour seems to affect simulated purchases, purchase rates and time spent in the store (Bellizzi and Hite, 1992). The ability to attract a shopper to retail is display (Bellizzi *et al.*, 1983). Based on the above discussions, we strongly advocate that there are no effects of extraneous variables (e.g., weather, competitor promotions) and confounding variables (stimuli of external, layout and design, point-of-purchase and decoration, and humans) to the validity of the empirical results.

Taking into consideration of above discussions, it can be concluded that none of the research carried out till now to quantify the influence of retail atmospherics on personalised shopper's behaviour, measure strategic and tactical value by measuring brick-and-mortar store performance in the form of footfall counting, conversation rate, UPT, and AOV, and measure personalised shopper's behaviour in the form of dwell time, purchase intention, emotional experience and remorse using cognitive computing based in-store analytics.

3. Theoretical background and hypotheses development

The atmosphere is referred to as a significant distinguishing component for stores compared to internet shops that can attract shoppers to the physical shop itself (van *et al.*, 2015). A theoretical background is therefore needed to determine the significance of the atmospheric factors.

3.1. Proposed theoretical model

The theoretical models based on retail atmospheric that have been proposed in existing literature are Rayburn and Voss (2013) proposed a model of the impact of hedonic and functional shopping evaluations of four conceptual environment constructs. The finding illustrates that the perceived atmosphere constructs are positively correlated with the retail shopping experience and the overall perception by the consumer that a store is a pleasant place is different for different retail brands. Foster and McLelland (2015) proposed a theme-based model to guide the manipulation of the atmospheric elements. The finding illustrates increases in shopping pleasure, positive attitudes to the brand, and brand loyalty. Roggeveen *et al.* (2020) proposed the DAST framework for retail atmospheres that extends conceptualizations to include not only in-store but also out-of-store experiences that retailers can control or influence. Eroglu *et al.* (2003) presented the S-O-R model to explain the role of atmospherics in the online retailing context. None of these theories addressed the personalisation of shoppers and store performance. Hence, we proposed a retail atmospherics model (called Personalised Retail Atmospherics Model), based on Forrest's Atmospherics Model (Van Vliet, 2018, p. 38) and presented in Fig. 1.

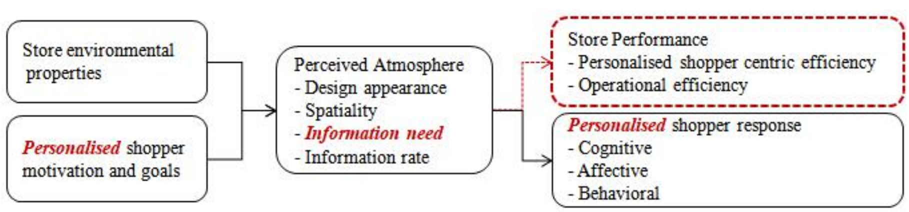

Fig. 1: Personalised Retail Atmospherics Model (adapted from Van Vliet, 2018)

The Forest model is primarily found in the research into museum experience that applies aspects such as motivations, values, expectations, a person's characteristics, experience, mood and involvement (Van

Vliet, 2018, p. 36). The model covers only a limited number of perceived atmosphere stimuli, resulting in the model being not easily characterised for future needs like seeking improvement areas in the near term or long term. Furthermore, the model does not encompass new insights by measuring the performance of the store and behaviour of personalised shoppers. In the proposed theoretical model, the add-on component is store performance, the add-on item is information need, and the renamed component is the personalised shopper response and personalised shopper motivation and goals. Store performance includes shopper-centric efficiency (building shopper loyalty, excellent shopper experience etc.) and operational efficiency (increase sales, boost profit, compete more effectively to defeat the cut-throat competition etc.). Information needs essentially is the information about the products, individual shopper's buying taste, purchase history and sales. If the store is at a loss, information need plays a bigger role to look at the data such as sales, inventory, shoppers and competitors to figure out an improvement area. Personalised shopper response can be cognitive (response of personalised shoppers that is generated on seeing an ad or word of mouth of the store which is evaluated in the light of past experiences, knowledge and attitudes) or/and affective (general psychological state of a shopper e.g., very good, good, neutral, bad very bad etc.) or/and behavioural (actions and interactions of the shopper try to maintain a balance). Personalised shopper motivation and goal is an individual's inclination toward shopping.

3.2. Conceptual model

The building blocks of suggested conceptual model are shopper personalisation and cognitive computing based in-store analytics platform.

3.2.1. *Shopper personalisation*

The personalisation of shoppers is presented in Fig. 2 and is founded on customer classification (Behera *et al.*, 2020).

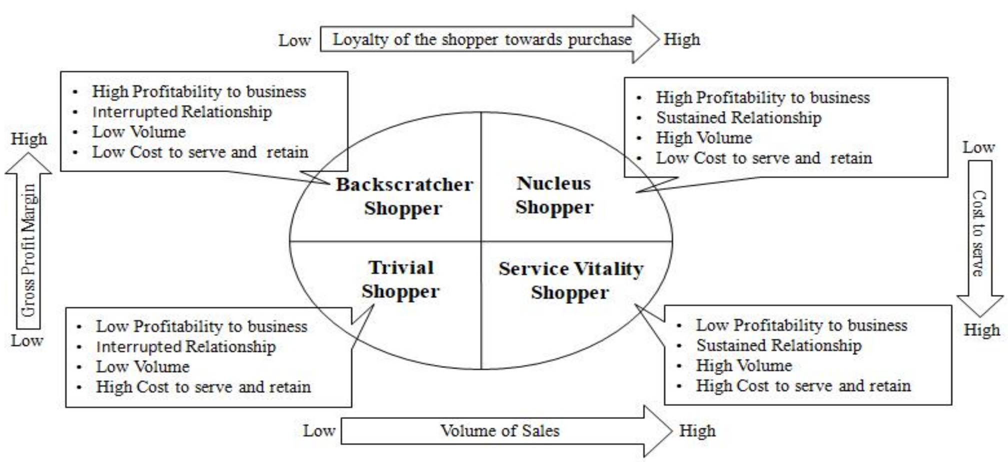

Fig. 2: Shopper personalisation (adapted from Behera *et al.*, 2020)

The shoppers are personalised as backscratcher shoppers, nucleus shoppers, trivial shoppers and service vitality shoppers. Such shopper's personalisation is exclusive to each other and collectively exhaustive. Shopper's dimensional spaces are transaction volume, loyalty to the store, business profitability, and service and retention costs. Dimensional spaces play an important role in shopper marketing. Shopper marketing achieves a win-win among shoppers and retailers (Shankar *et al.*, 2011) and we advocate that shopper marketing has an immediate effect and direct influence on shopper behaviour. Nucleus shopper is characterised by high profitability, sustained relationship, the high volume of purchase and low cost to serve and retain. Similarly, the characteristics of other shoppers can be comprehended from Fig. 2.

The clustering approach is used to group together similar data and k-mean clustering is a popular method used for segmentation (Rauf *et al.*, 2012), but it is applicable to only numeric data (Ahmad and Dey, 2007). The retailer may not guarantee to define the dimensional spaces like loyalty to the store, business profitability etc. to be numeric features, and can be categorical. Therefore, we propose enhanced k-mean clustering unsupervised ML algorithm by Ahmad and Dey (2007) for shopper personalisation, grounded on proposed dimensional spaces. The enhanced k-mean clustering algorithm is taken into account of numeric and categorical features, effective in comparison to other clustering algorithm (Ahmad and Dey, 2007) and has been effectively tested (Caruso *et al.*, 2021; Ansari *et al.*, 2021; Lee *et al.*, 2021).

3.2.2. In-store cognitive computing based analytics platform

The cognitive computing based in-store analytics platform is presented in Fig. 3, depicting different components and interactions among those, followed by a qualitative data classification algorithm. The proposed platform is a group of technological components that are used as a base upon which in-store cognitive computing based analytics can be achieved to enable the retailers in delivering the outcomes needed to transform the brick-and-mortar store performance and personalised shopper's behaviour. The platform connects tools, teams, data, and processes of brick-and-mortar store under one digital roof.

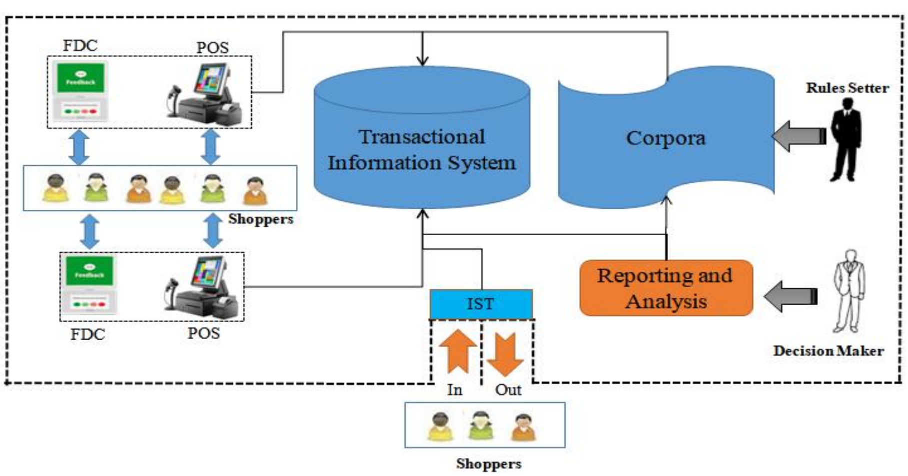

Fig. 3: Cognitive computing based in-store analytics platform

The in-store analytical platform consists of descriptive analytics to measure the store performance, dwell time of shopper satisfaction, and cognitive analytics involving processing of text to measure purchase intention, emotional experience, and remorse of shopper satisfaction using a text classification algorithm. The actors of the platform are shopper, rules setter and decision maker. The shoppers are the customers who visit the store and make purchases, the rules setter are the individuals who define the rules for brick-and-mortar store/business operations and the decision makers are the individual who makes wide range of decisions related to shopper, tactical, business, policy, personal etc. Different components of the cognitive computing based in-store analytics platform are presented in Table I.

Table I: Components of cognitive computing based in-store analytics platform

Component	Description
In-store tracking (IST)	IST is a technique to track shopper entry, exit, and time spent in the store. The technique uses a combination of in-store cameras and facial analysis software. Using such a technique, core data related to the shopper, collected at each stage of the shopping journey, tracking shoppers from browsing through checkout. Such quantitative data is then forwarded to a central server (Transactional Information System) where it is processed and analysed.
Point of sale (POS)	POS is the place in the brick-and-mortar store where the transaction is carried out between a shopper and merchant when a product is purchased. Merchants use a POS system to complete a sales transaction. Such quantitative data is then forwarded to Transactional Information System where it is processed and analysed.
Feedback data collector (FDC)	FDC is a system where shoppers answer a questionnaire to gain valuable insight into an atmospheric stimuli, emotional experience, purchase intention, and remorse. Such qualitative and quantitative data is then forwarded to Transactional Information System where it is processed and analysed.
Transactional Information System (TIS)	It is the system to store transactional data, collected from IST, POS, FDC and corpora in the raw and summarized format. The data is stored systematically and consistently for easier and faster processing for reporting and analysis.
Corpora	It is the knowledge base to house business rules like for which products to cut prices to compete especially in a tight economy, the fair and consistent return policy of the store, whether to allow layaway purchases, whether to allow extended hours during the holiday shopping season, handling returned checks, shopper classification and discount percentage for each personalised shopper. It may additionally include ontologies (e.g., shopper, product hierarchy) to define specific entities and relationship.
Reporting and analysis	The reporting translate shopper behavioural and store performance data into usable information and analysis explore such information to extract meaningful insights for time bound decision-making process.

A popular implementation of Naive Bayes (Rish, 2001) for NLP involves processing the text using Term Frequency-Inverse Document Frequency i.e., TF-IDF (Ramos, 2003) and then running the multinomial naive Bayes on it. The algorithm is applied to the textual data for determining shopper opinion of purchase intention, emotional experience, and remorse. The class of the text collected from purchase intention, emotional experience, and remorse is classified and defined as a value (2 or 1) that expresses whether an expressed opinion is positive (value = 2), or negative (value = 1). Naive Bayes classifiers are linear classifiers recognised as efficient classifiers (Raschka, 2014) and tend to perform very well under this unrealistic assumption (Rish, 2001). The classifier has been effectively tested in text categorization (Sahami *et al.*, 1998).

3.3. Hypothesis research model

Turley and Milliman (2000) proposed a list of atmospheric stimuli and grouped them into five categories such as external, general interior, layout and design, point-of-purchase and decoration, and humans. Our study is scoped to the retail atmospherics that relates to general interior stimuli comprising of cleanliness, music, scent, temperature, lighting, and colour. Overall impressions of the general interior stimuli were examined by (Donovan *et al.*, 1994, Akhter *et al.*, 1994; Ward *et al.*, 1992; Grossbart *et al.*, 1990) and indicated that such stimuli affect the time spent in the environment by the shopper and the sales. The definition and source for each construct are conceptualised in Table II. The table also capture the causal effect to the outcome.

Table II: Construct conceptualisation

Component	Description
Footfall count	It is the measurement of the number of shoppers entering the brick-and-mortar store for a particular time (Noad and Rogers, 2008). A higher value represents better purchasing opportunities by the shoppers and better alignment of store staff.
Conversation Rate	It is the measurement of the proportion of shoppers who make purchases (Dennis and Newman, 2005). A higher value represents an increased sale.
UPT	It is the measurement of the number of items purchased per single transaction (Santos, 2011). A higher value represents increased sales, improved store performance, better sales decisions and improved shopper experience.
AOV	It is the measurement of the average amount spent each time a shopper makes a transaction (Behera *et al.*, 2020). A higher value represents a reduction of the payback period and increased return on investment.
Dwell Time	It is the actual length of the time the shoppers spend in the brick-and-mortar store before leaving the store (Morrison *et al.*, 2011). A higher value represents the shopper's happiness and satisfaction.
Purchase Intention	It is the likelihood of a shopper buying the same product again based on the purchase history (Hussain and Ali, 2015). A higher value represents the need for the product which is driving the shopper towards a purchase.
Emotional Experience	It is the measurement of positive or negative in-store emotional experience (Andreu *et al.*, 2006). A higher value represents the increase in dwell time, footfall count, and most importantly, an increase in sales.
Remorse	When a shopper buys an expensive product and feels that a wrong choice is made, then the feeling of guilt in the mind is called the shopper's remorse (Ortinau *et al.*, 2013). A lower value is directly related to the importance of the purchase.

The study discussed eight hypotheses. Fig. 4 depicts the hypothesis research model, based on hypotheses and constructs. Hypotheses H1 to H4 relates to store performance and H5 to H8 relates to shopper satisfaction in the research model. The + symbol represents the positive and – symbol represents the negative relationship among the constructs.

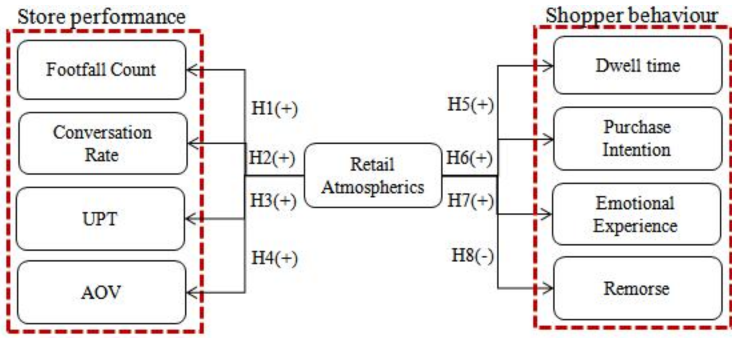

Fig. 4: Hypothesis research model (adapted from Noad and Rogers, 2008; Dennis and Newman, 2005; Santos, 2011; Behera *et al.*, 2020; Morrison *et al.*, 2011; Hussain and Ali, 2015; Andreu *et al.*, 2006; Ortinau *et al.*, 2013; Van Vliet, 2018)

3.4. Hypotheses development

The study aims to validate each research question (RQ) through testable and empirical hypotheses. Therefore, RQ1 relates to the hypotheses H1 to H4 and RQ2 relates to the hypotheses H5 to H8. Each hypothesis is discussed below and articulated the role of retail atmospherics on store performance and shopper behaviour.

3.4.1. Footfall count of store

A higher value of the footfall count means a boost in sales productivity and improvement in the store performance. Research suggests that store performance is related to pedestrian movement and footfall count is one of the most important criteria to attract shoppers to the stores (Timmermans *et al.*, 1992). Based on the footfall received during weekdays and weekends, malls are pricing their shops (Krishna, 2014). The footfall count would increase if the store atmosphere is better (Hassan, 2015). We advocate footfall count helps the store to analyse the store traffic with real-time numbers. Hence, evaluating the success of store performance cannot be based solely on sales figures, so increased foot traffic needs to be considered. Increasing footfall count in a brick-and-mortar store can be divided into two categories: motivating existing shoppers to return to the business and increasing brand recognition among new shoppers. Retail atmospherics can facilitate the increase of shopper's footfall count by making changes including leaving the front door open, which can help shoppers feel more approachable and encourage them to enter, window displays that are as smart as possible and in keeping with the season, changing interior displays every few weeks and ensuring that seasonal items are removed as soon as they are no longer relevant, creating an attractive storefront and appropriate usage of general interior stimuli. Therefore, it is hypothesised:

H1. Retail atmospherics facilitate the increase of shopper's footfall count for a brick-and-mortar store.

3.4.2. Conversation rate of store

A higher value of the conversation rate means better understanding of the shoppers, boost sales, stealing shoppers from competitors, and improvement in brand perception. Research suggests that store sales have a concave traffic connection, with conversion rates dropped non-linearly as traffic increases (Mani and Swaminathan, 2015). Improving shopper conversion rates has become a challenge for retailers (Dave and Sondhi, 2011). Global retailers can create a greater store-fitting that suits their international image by using music played in English and increase overall conversion rates (Toldos *et al.*, 2019). We advocate that a high conversion rate is indicative of successful marketing leading to a better customer experience with higher store performance. Retail atmospherics can facilitate the increase of shopper's conversation rates by making changes including proper design of checkout lines to lower the waiting time, placement of display smack-dab in the middle of walkways, display of stocks with high-margin items, and clean, wide, easily navigable aisles to help shoppers move quickly and freely and appropriate usage of general interior stimuli. Therefore, it is hypothesised:

H2. Retail atmospherics facilitate the increase of shopper's conversation rates for a brick-and-mortar store.

3.4.3. Units per transaction (UPT) of store

A higher value of UPT means more items the shoppers are purchasing in every visit, which inadvertently increase the average transaction value. Research suggests that for many retailers, the sales strategy is to increase UPT (Palan and Mallalieu, 2012; Jaykumar, 2016). We advocate that the higher the UPT, the more items shoppers are purchasing for every visit and retailers often use it to evaluate sales trends. Retail atmospherics can facilitate the increase of UPT by making changes including the display of impulse purchases and gift cards near the register, creating appealing customer surroundings with visual merchandising, good lighting to enhance aesthetic appearance, keeping small and impulse purchases near the billing counter, and appropriate usage of general interior stimuli. Therefore, it is hypothesised:

H3. Retail atmospherics facilitate the increase of units per transaction (UPT) for a brick-and-mortar store.

3.4.4. Average order value (AOV) of the store

A higher value of AOV means an increase in revenue and profit margins. Research suggests that AOV is continuing to be cited as a key indicator of success for the retailer (Wulfken, 2018). We advocate that AOV helps retailers to evaluate marketing effort, and pricing strategy and is the key performance indicator that retailer measures to understand shopper's purchasing habits and then decide to scale profit, and revenue growth. It is also helpful to target high value or low-value shoppers. Retail atmospherics can facilitate the increase of AOV by making changes including creating an eye-catching display by highlighting trending items, highlighting shopper recommendations along with testimonials, highlighting best-seller items, display of mix and match offers and appropriate usage of general interior stimuli. Therefore, it is hypothesised:

H4. Retail atmospherics facilitate the increase of average order value (AOV) for a brick-and-mortar store.

3.4.5. Dwell time of personalised shopper

A higher value of dwell time means increase insight for up-sell and cross-sell profits and an increase in in-store conversions. Research suggests that analysis of dwell time includes knowing where customers go and remain in a shop and are as essential as counting those (Connell *et al.*, 2013). It is reasonable to connect the dwelling time to the shop area for supermarkets, department shops and in small supermarkets (De *et al.*, 2014). We advocate that the longer the dwell time the better, as this indicates that the shoppers have stayed mostly in the store and more likely they are to buy items. It can also be used to analyse shopping behaviour and monitor an increase in shopper spending. Retail atmospherics can facilitate the increase of personalised shopper's dwell time by making changes including designating an area of the store to interact with the products, utilizing interactive displays, providing a way for shoppers to carry multiple items, offering in-store services exclusively, serving coffee or tea, injecting worthy features into space, engaging the kids by devoting some section while the parents do their shopping and appropriate usage of general interior stimuli. Therefore, it is hypothesised:

H5. Retail atmospherics in a brick-and-mortar store facilitates the increase of personalised shopper's dwell time.

3.4.6. Purchase intention of personalised shopper

A higher value of purchase intention means growth in the higher transaction, which will lead to increased profitability. Research suggests that shopper responses induced by changes in atmospheric variables include an increase in purchase intentions (Areni *et al.*, 1999). A higher value of purchase intention means growth in the higher transaction which will lead to increased profitability (Schiffman and Kanuk, 2007). We advocate that store environment has a positive effect on shopper purchase decisions. Store atmosphere and impulse buying both relate to shopper buying behaviour. Retail atmospherics can facilitate the increase of personalised shopper's purchase intention by making changes including choosing the right music, choosing the appropriate lighting, effective usage of hotspots and appropriate usage of general interior stimuli. Therefore, it is hypothesised:

H6. Retail atmospherics in a brick-and-mortar store facilitates the increase of personalised shopper's purchase intention.

3.4.7. Emotional experience of personalised shopper

A higher value of emotional experience means an increase in trust-building with the shopper, which leads to increase loyalty and less abandonment to the brand. Research suggests that the auditory environment influence the amount of stimulation, mood (Alpert and Alpert, 1990) and emotions (Konečni, 2008) of a shopper. Shoppers spend more time in environments they find enjoyable or where time seems to move more slowly (Spence *et al.*, 2014). We advocate that the store environment will boost retail sales with emotional engagement with the personalised shoppers. Retail atmospherics can facilitate the increase of personalised shopper's emotional experience by making changes including playing appropriate music that can make shoppers pay more attention to their preferences and attitudes and less to product attributes such as price, physical warmth to increase willingness-to-pay for items by activating a sense of emotional warmth, frictionless checkout to eliminate barriers during shopping, display of saving information and appropriate usage of general interior stimuli. Therefore, it is hypothesised:

H7. Retail atmospherics in a brick-and-mortar store facilitates the increase of personalised shopper's emotional experience.

3.4.8. Remorse of personalised shopper

A lower value of remorse means a higher percentage of repeat shoppers and pay off in terms of a healthier brand reputation and long-term sales. Research suggests that everyone experiences the remorse of the shopper to some extent, with each purchase and the remorse of the shopper, often leading to returns or cancellations of purchases (Friedman, 2011). The remorse of the buyer can also be manifested in consumers when they make a decision and then regret the fact that they make that decision (Kros and Brown, 2012). Increased spending increased post-purchase remorse for customers, which could invoke negative attitudes (Nordfält *et al.*, 2004). We advocate that stores do everything to prevent personalised shopper's remorse to develop sustained relationships that expand the value in the bottom line over the long haul. Retail atmospherics can facilitate the decrease of personalised shopper's remorse by first recognizing that it exists. After acknowledging, the shopper's remorse gap to be determined. During the process, a pleasant store environment and appropriate usage of general interior stimuli can decrease shopper's remorse while showcasing the examples of shoppers who enjoyed the items. Personalised *s*hopper's reviews in a pleasant store environment can remove doubts that they may have about the purchased item. If a personalised shopper's remorse cannot be eliminated, at least an attempt should be made to reduce it by playing preferred music, applying pleasant ambient scents when it is semantically compatible with the item, applying various forms of lighting to modify brain function patterns. Therefore, it is hypothesised:

H8. Retail atmospherics in a brick-and-mortar store facilitate the decrease of personalised shopper's remorse.

4. Methodology

4.1. Data sources

The data were collected with face-to-face interviews with the shoppers from an anonymous brick-and-mortar store (Indian retailer) that sells products in the categories of personal care, food, beauty and baby products. Since the authors are from India, their personal contact information was used for identification of the store and shoppers. The retailer roughly controls 1100 stores (as of 2021) across 500 cities and is growing rapidly. It has more than 15 million customers and also has digital presence. Aggressive store addition and sales is the primary driver of the revenue growth of the retailer. To keep the registered/trusted customers happy, the store either calls or sends latest offers over email/SMS (short message service).

4.2. Data collection

The interview was conducted by five interviewers, who were well trained for conducting the personal interview in English. Individual shopper's data comprising of 9 predictors/features (i.e., footfall in datetime, footfall out datetime, whether purchase made, unique items purchased, average order value of the purchase, purchase intention, emotional experience, remorse and retail atmosphere stimuli) were considered for the survey. The shoppers were requested for the participation during their physical visit to the store and data were collected from the known population. The known population is the shoppers who registered with the store and during payment, share the mobile number. The unknown population is the shoppers who do not register with the store and hence, do not share their mobile number during the purchase process. The unknown universe is out of the scope of this study. The participants were given a choice to fill out the survey after the purchase or while exit from the store. The shoppers were interviewed after the entry to the store and the interviewers articulated the purpose of the study. The questionnaire was used to create a template and it consisted of a set of questions printed in a specific order on a paper-based form, which the respondent completed independently.

Several challenges were faced while collecting consistent and quality data and therefore, we followed a practical, law-compatible process and appropriate precautions were undertaken to overcome those, such as a letter of consent, keeping the language and format of the survey simple, the anonymity of respondent, time break during the face-to-face interview, offered support while filling responses, and remain flexible to interview time.

One month of data (October 2020) were gathered before the implementation of the suggested model. Then, one month (November 2020) of data were gathered after the suggested approach was implemented. In November 2020, the store played festival songs, coated with festive decorations, flags, chocolates, gifts, sacred threads, and the colourful special band were placed in racks and stacks that were easily accessible. An eco-friendly cleaning spray was used to keep the store out of bad odours. The store was mandated in meeting or exceeding the ventilation requirements.

4.3. Sampling

Post to the identification of brick-and-mortar store, the interviewers interacted with those shoppers who are conveniently available to participate in the study. The convenience sampling technique was used to access the data as (Ruhl, 2004) it has been generally accepted and is cost-effective. For this empirical study, the shoppers were personalised based on the monthly purchase history and are shown in Table III. In total, 35 shoppers participated in the study with 294 samples collected from such shoppers. Concerning t-test, a method of calculation for the sample size (Green, 1991) is $n \geq 50 + 8 * p$, where n is the sample size and p is the number of predictors. For this study, the number of predictors is 9. The application of the method results a sample size 122 (i.e., 50 + 8* 9) and the study has considered 294. In this table, MPA stands for the monthly purchase amount in Indian Rupees (INR) and the aggregated MPA figure was shared by the store, based on the consent of shopper.

Table III. Shopper personalisation

Sr #	Shopper	MPA	No. of shoppers	No. of samples
1	Nucleus	More than 20 K	3	28
2	Service Vitality	Between 9K to 20 K	7	98
3	Backscratcher	Between 1.6K to 9K	10	90
4	Trivial	Less than 1.6K	15	78
Total	**…………………………………………..**		35	294

4.4. Survey instruments

For the retail atmosphere, the questionnaire is open-ended Likert scale 5-point scaling questions wherein strongly agree represents scale 5, agree represents scale 4, reasonably well represents scale 3, disagree represents scale 2, and strongly disagree represents scale 1. The objective is to measure personalised shopper's perception of the retail atmosphere stimuli. Table AI in Appendix A represents the question set that is common to purchase intention, emotional experience, and remorse. The questionnaire additionally includes closed-ended questions for purchase intention, emotional experience, and remorse, and the objective is to perform cognitive analytics using Naive Bayes. Table AII in Appendix A represents the question set for purchase intention, Table AIII in Appendix A represents emotional experience, and Table AIV in Appendix A represents remorse. In Table AI, the questions were designed based on (Hussain and Ali, 2015).

4.5. Data analysis

One of the most commonly used statistical hypothesis tests is the t-test (Yim *et al.*, 2010), hence we adopted it. A one-sample t-test is performed to compare the mean of convenience sample with the known universe by keeping a p-value of .05 for the acceptance of data validity. In most cases, a p-value of less than .05 (5%) is accepted to denote the validity of the data (Blanchard *et al.*, 2011). For this study, UPT is considered to be the number of unique units per transaction. The unit of measurement of dwell time is minutes and AOV is Indian rupees.

For store performance and dwell time, the null hypothesis (H_0) is the convenience sample mean, which is equal to the known universe mean, and the alternative hypothesis (H_a) is the known universe mean, which is either greater or less than the convenience sample mean. For purchase intention, emotional experience and remorse, the null hypothesis (H_0) is the convenience sample mean, which is equal to the positive class (coded as 2) and the alternative hypothesis (H_a) is the convenience sample mean, which is either greater or less than the positive class. The positive or negative class is the outcome of the Naive Bayes text classification algorithm. The pre and post-test summary statistics are presented for the store performance and shopper satisfaction. Then, insight analysis is performed to demonstrate the effectiveness of the proposed approach. The hypothesis result of store performance in the form of footfall count (H1), conversation rate (H2), UPT (H3), and AOV (H4) determine the validity of the first research question and the hypothesis result of shopper satisfaction in the form of dwell time (H5), purchase intention (H6), emotional experience (H7), and remorse (H8) meets the validity of second research question.

Also, advance analysis is performed to demonstrate the strategic decisions of the store and the tactical value of the personalised shopper with SWOT (strengths, weaknesses, opportunities, and threats). The SWOT analysis is the commonly accepted instrument for carrying out strategic marketing decision-making (Phadermrod *et al.*, 2019; Ayub *et al.*, 2013).

5. Results

The result of this study is presented with summary statistics (i.e., before and after the implementation of the proposed model, and the effectiveness of the model), hypotheses results and the validity of research questions, and strategic analysis with SWOT.

5.1. Summary Statistics

This section presented the descriptive analytics result of one month of data for the experiment before, after the implementation of the proposed model and the effectiveness of the model. The value marked with an asterisk (i.e., ***) represents a p-value of less than .001.

5.1.1. Summary of data before the implementation of the proposed model

This section outlined the descriptive analytics of one month of data (October 2020) before the proposed model was implemented. In respective tables (i.e., Table IV to Table VI), NS represents a nucleus shopper, SVS represents a service vitality shopper, BS represents a backscratcher shopper, and TS represents a trivial shopper. From Table IV, it can be concluded that the p-value is less than .05, thus meeting the data validity.

Table IV. Descriptive analytics for store performance and dwell time

Measurement	Parameter ▼	NS	SVS	BS	TS
Footfall count			*Convenience Sample*		
	Mean	3	6	4	2
	Standard Deviation	1	1	1	1
	Max	5	7	5	3
	Min	3	5	2	1
			Known Universe (Population)		
	p-value	.03	.01	.01	***
	Mean	7	5	5	3
Conversation Rate			*Convenience Sample*		
	Mean	41%	38%	33%	36%
	Standard Deviation	9%	4%	9%	20%
	Max	50%	43%	50%	50%
	Min	33%	33%	20%	0%

		Known Universe (Population)			
	p-value	***	.02	.01	.01
	Mean	20%	33%	24%	22%
UPT		*Convenience Sample*			
	Mean	101	74	10	4
	Standard Deviation	2	3	2	3
	Max	103	78	14	11
	Min	100	70	7	0
		Known Universe (Population)			
	p-value	.01	.01	.02	***
	Mean	108	71	12	7
AOV		*Convenience Sample*			
	Mean	25124	12082	1984	522
	Standard Deviation	3132	1570	506	447
	Max	28300	13740	2915	1350
	Min	22037	8955	1323	0
		Known Universe (Population)			
	p-value	.04	.03	.01	.04
	Mean	33000	10500	1500	775
Dwell time		*Convenience Sample*			
	Mean	49	42	35	25
	Standard Deviation	2	1	1	3
	Max	51	44	39	30
	Min	48	40	34	20
		Known Universe (Population)			
	p-value	.03	.01	0.01	0.02
	Mean	44	44	34	27

The descriptive analytics i.e., mean scale value of common questions (Q1 to Q26 in Table AI of Appendix A) for purchase intention, emotional experience, and remorse of the experiment is presented in Table V and it depicts that the shoppers are rated "reasonably well" to the retail atmospherics. Rating for each class of shoppers can be easily comprehended from it.

Table V. Common questions descriptive analytics for shopper satisfaction

Sr #	Retail Atmospherics ▼	NS	SVS	BS	TS	Mean	Interpretation
1	Cleanliness	2.75	3.14	2.5	3.15	2.88	reasonably well
2	Music	2.83	3.11	3.01	2.84	2.94	reasonably well
3	Scent	2.33	3.35	3.17	3.03	2.97	reasonably well
4	Temperature	4.1	4.03	4	4.05	4.04	agree
5	Lighting	3.2	3.14	3	3.01	3.08	reasonably well
6	Colour	2.55	2.71	3.2	2.66	2.78	reasonably well
Retail Atmospherics Mean		2.96	3.24	3.14	3.12	3.11	reasonably well

By considering the retail atmospherics (outlined in Table V), the outcome of cognitive analytics for purchase intention by including response to the question (Q1 from Table AII of Appendix A), emotional experience by including response to the question (Q1 from Table AIII of Appendix A), and remorse by including response to the questions (Q1 and Q2 from Table AIV of Appendix A) is presented in Table VI. Due to the non-availability of known universe data, the p-value for personalised shoppers was not feasible.

Table VI. Opinion for shopper satisfaction

Sr #	Measurement of ▼	Class ▼	NS	SVS	BS	TS	Mean

1	Purchase intention		*Convenience Sample*				
		Total	3	6	8	12	7
		Positive	2	3	6	8	5
		Negative	1	3	2	4	2
% of positive class…………………………...			67%	50%	75%	63%	71%
The positive class p-value for purchase intention ………………………………………..							.0001
2	Emotional experience		*Convenience Sample*				
		Total	3	6	8	12	8
		Positive	2	4	5	7	5
		Negative	1	2	3	5	3
% of positive class…………………………...			67%	67%	62%	58%	62%
The positive class p-value for emotional experience.…………………………………….							***
3	Remorse		*Convenience Sample*				
		Total	1	3	4	5	3
		Positive	0	0	2	1	1
		Negative	1	3	2	4	2
% of positive class……………………….			0%	0%	50%	20%	33%
The positive class p-value for remorse ......…………………………………………………..							.04

5.1.2. Summary of data post to the implementation of the proposed model

This section outlined the descriptive analytics of one month of data (November 2020) after the implementation of proposed model. In respective tables (Table VII to Table IX), NS represents a nucleus shopper, the SVS represents a service vitality shopper, BS represents a backscratcher shopper, and TS represents a trivial shopper. From Table VII, it can be concluded that the p-value is less than .05, thus meeting the data validity.

Table VII. Summary for store performance and dwell time

Measurement	Parameter ▼	NS	SVS	BS	TS
Footfall count		*Convenience Sample*			
	Mean	5	8	5	3
	Standard Deviation	1	1	1	1
	Max	6	9	6	5
	Min	4	6	4	1
		Known Universe (Population)			
	p-value	0.02	***	***	***
	Mean	9	10	6	4
Conversation rate		*Convenience Sample*			
	Mean	48%	44%	42%	44%
	Standard Deviation	14%	7%	10%	21%
	Max	60%	56%	60%	100%
	Min	33%	33%	25%	25%
		Known Universe (Population)			
	p-value	.01	.02	.02	.01
	Mean	25%	35%	33%	30%
UPT		*Convenience Sample*			
	Mean	107	79	12	7
	Standard Deviation	5	6	1	2
	Max	112	86	13	10
	Min	102	73	9	4
		Known Universe (Population)			
	p-value	.03	.01	***	.04
	Mean	122	72	10	8

AOV		*Convenience Sample*			
	Mean	27398	13436	2183	839
	Standard Deviation	712	1074	212	312
	Max	28125	14448	2602	1650
	Min	26702	11537	2039	421
		Known Universe (Population)			
	p-value	.02	.01	.02	.03
	Mean	30000	12000	2000	1025
Dwell time		*Convenience Sample*			
	Mean	53	46	38	29
	Standard Deviation	3	11	4	4
	Max	56	61	48	38
	Min	51	31	35	20
		Known Universe (Population)			
	p-value	.01	.01	.03	.01
	Mean	65	60	41	32

The descriptive responses i.e., mean scale of common questions (Q1 to Q26 in Table AI of Appendix A) for purchase intention, emotional experience, and remorse recorded for November 2020 are presented in Table VIII and it shows that shoppers have rated differently to the retail atmospherics. Rating for each class of shoppers can be easily comprehended from it.

Table VIII. Mean of common questions for shopper satisfaction

Sr #	Retail Atmospherics ▼	NS	SVS	BS	TS	Mean	Interpretation
1	Cleanliness	4.75	4.82	4.75	4.68	4.75	strongly agree
2	Music	4.11	4.30	4.2	4.22	4.2	agree
3	Scent	4.75	4.6	4.67	4.67	4.67	strongly agree
4	Temperature	4.5	4.28	4.3	4.16	4.31	agree
5	Lighting	3.8	4.02	3.88	3.85	3.88	reasonably well
6	Colour	3.66	3.57	3.73	3.84	3.7	reasonably well
Retail Atmospherics Mean		4.26	4.26	4.25	4.23	4.25	agree

The cognitive opinion of open-ended questions for purchase intention (Q1 in Table AII of Appendix A), emotional experience (Q1 in Table AIII of Appendix A), and remorse (Q1 and Q2 in Table AIV of Appendix A) recorded for November 2020 is presented in Table IX. Due to the non-availability of known universe data, the p-value for each shopper was not feasible.

Table IX. Opinion for shopper satisfaction

Sr #	Measurement of ▼	Opinion	NS	SVS	BS	TS	Mean
1	Purchase intention			*Convenience Sample*			
		Total	3	7	10	15	9
		Positive	3	5	8	11	7
		Negative	0	2	2	4	2
% of positive class ……………………			100%	71.4%	80%	73%	81%
The positive class p-value for purchase intention ………………………………………..							.0009
2	Emotional experience			*Convenience Sample*			
		Total	3	7	10	15	9
		Positive	3	6	9	12	8
		Negative	0	1	1	3	1
% of positive class ……………………			100%	86%	90%	80%	89%
The positive class p-value for emotional experience.…………………………………….							0.012
3	Remorse			*Convenience Sample*			

	Total	3	7	10	15	9
	Positive	0	1	2	2	1
	Negative	3	6	8	13	8
% of positive class ………………………		0%	14%	20%	13%	11%
The positive class p-value for remorse ………………………………………………………..						.012

5.1.3. *Effectiveness*

The effectiveness of the proposed approach is measured with the mean difference of footfall count, conversation rate, UPT, AOV, dwell time, purchase intention, emotional experience, and remorse for the timeframe October 2020 in comparison with November 2020. Table X(a) depicts footfall count positively influences store performance with a 46% month-on-month growth, wherein 54% growth was observed for the nucleus, 33% for service vitality, 38% for backscratcher and 59% for trivial shoppers. Maximum growth was observed for trivial and minimum growth was observed for service vitality shopper. In a similar notation, the % difference of others can be quickly comprehended from the table. It can be observed that in all cases the difference is positive except for remorse and therefore it can be concluded that the proposed approach is effective.

Table X(a). Testing result of footfall count

Shopper	Feb 20	Mar 20	%diff
Nucleus	3	5	54%
Service Vitality	6	8	33%
Backscratcher	4	5	38%
Trivial	2	3	59%
Footfall count diff………..…..…..…			46%

Table X(b): Testing result of conversation rate

Shopper	Feb 20	Mar 20	%diff
Nucleus	41%	48%	17%
Service Vitality	38%	44%	16%
Backscratcher	33%	42%	27%
Trivial	36%	44%	22%
Conversation rate diff………..…..			21%

Table X(c). Testing result of UPT

Shopper	Feb 20	Mar 20	%diff
Nucleus	101	107	6%
Service Vitality	74	79	7%
Backscratcher	10	12	20%
Trivial	4	7	75%
UPT overall diff……………………..……..			27%

Table X(d). Testing result of AOV

Shopper	Feb 20	Mar 20	%diff
Nucleus	25124	27398	9%
Service Vitality	12082	13436	11%
Backscratcher	1984	2183	10%
Trivial	522	839	61%
AOV overall diff……………………..…….			23%

Table X(e). Testing result of dwell time

Shopper	Feb 20	Mar 20	%diff
Nucleus	49	53	8%
Service Vitality	42	46	10%
Backscratcher	35	38	9%
Trivial	25	29	16%
Dwell time overall diff………………...			11%

Table X(f). Testing result of purchase intention

Shopper	Feb 20	Mar 20	%diff
Nucleus	67%	100%	49%
Service Vitality	50%	71%	42%
Backscratcher	75%	80%	7%
Trivial	63%	73%	16%
Purchase intention overall diff…..…..…...			29%

Table X(g). Testing result of emotional experience

Shopper	Feb 20	Mar 20	%diff
Nucleus	67%	100%	49%
Service Vitality	67%	86%	28%
Backscratcher	62%	90%	45%
Trivial	58%	80%	38%

Table X(h). Testing result of remorse

Shopper	Feb 20	Mar 20	%diff
Nucleus	0%	0%	0%
Service Vitality	0%	14%	14%
Backscratcher	50%	20%	(60%)
Trivial	20%	13%	(35%)

Emotional experience overall diff……	40%	**Remorse overall diff…………………**	(20%)

Note: In Table X(h), negative numbers are shown in the bracket.

5.2. Hypotheses results and validity of research questions

A p-value of less than 0.05 signifies to accept the hypothesis (Zaykin *et al.*, 2002). Table XI depicts the hypotheses testing result of store performance and dwell time for personalised shoppers and is the inference from Table VI.

Table XI: Hypotheses testing result of store performance and dwell time

Shopper	Footfall count	Conversation rate	UPT	AOV	Dwell time
Nucleus	.02	.01	.03	.02	.01
Service Vitality	***	.02	.01	.01	.01
Backscratcher	***	.02	***	.02	.03
Trivial	***	.01	.04	.03	.01

The p-value is less than .05 and hence the hypotheses H1 (footfall count), H2 (conversation rate), H3 (UPT), H4 (AOV), and H5 (dwell time) were supported in the study. Table IX shows that the p-value for purchase intention is .0009, emotional experience is .012, and remorse is .012, hence hypotheses H6 (purchase intention), H7 (emotional experience), and H8 (remorse) were supported in the study. Thus, the research questions of atmospheric effect on brick-and-mortar store performance (RQ1) and shopper satisfaction (RQ2) is achieved with the support of hypotheses H1 to H4, and H5 to H8 respectively.

5.3. Strategic Analysis

Using diagnostics analytics, the study has discovered an indirect causal relation between footfall count (FC) → dwell time (DT) → UPT i.e., the cause is footfall count and the effect is UPT through dwell time. The indirect causal relation was recorded for November 2020. The correlation coefficient (r) in the range of 0.36 to 0.67 represents modest, and 0.68 to 1.0 represent strong correlations (Taylor, 1990). FC ~ DT exhibited a value of 0.52, thus signifies modest correlations. DT ~ UPT exhibited a value of 0.76 and signifies strong correlations.

Based on the empirical result, the study investigated the strategic decision of the store and tactical value of the personalised shopper with SWOT analysis and is presented in Fig. 5. The figure explains the strength offered by the personalised shopper in achieving business objectives with general interior atmospheric stimuli. In a similar notation, weakness, opportunists, and threats can be comprehended.

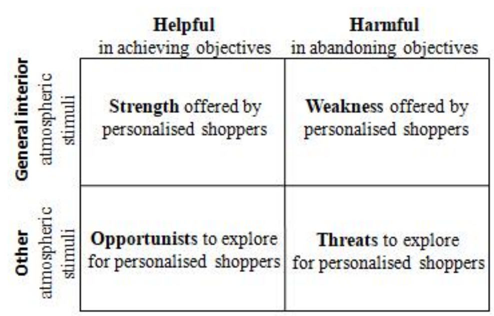

Fig. 5: SWOT analysis of store strategic decision and personalised shopper tactical value

From store performance, radical growth was observed for trivial shoppers followed by backscratcher shoppers. In the SWOT analysis, such shoppers may be considered as strengths in achieving business objectives. The study witnessed conservative growth for nucleus, service vitality shoppers and such shoppers should not be placed into weakness and rather attempts should be made by retailers to move them to the strength quadrant.

From personalised shopper behaviour, radical growth was observed for backscratcher shoppers, followed by trivial shoppers. In the SWOT analysis, such shoppers may be considered as strengths in the tactical value of achieving business objectives.

From retail atmospheric stimuli, radical growth was observed in cleanliness, music, and scent atmospheric stimuli for nucleus shopper, backscratcher shopper, and trivial shopper, and conservative growth was observed in temperature, lighting, and colour for backscratcher shopper. With the SWOT analysis, the former may be considered as strength and the latter can be considered as a weakness.

6. Discussion

The hypotheses H1 (footfall count), H2 (conversation rate), H3 (UPT), H4 (AOV), H5 (dwell time), H6 (purchase intention), H7 (emotional experience), and H8 (remorse) were supported in the study, thus it can be concluded that retail atmospherics influence the store performance and behaviour of personalised shoppers.

This study highlights contributions in support of or against the previous studies and contributions to the body of knowledge. In the experiment, radical growth was observed for cleanliness, and scent feature (refer Table XI) and hence this study explores such features. The data in the table is the inference of Table V and Table VIII and represents the mean scale value of common questions (Q1 to Q26 in Table A1 of Appendix A) for purchase intention, emotional experience, and remorse.

Table XI: Retail atmospherics effects (before vs. after)

Sr #	Atmospheric Feature	Experiment Before	After
1	Cleanliness	reasonably well	strongly agree
2	Music	reasonably well	Agree
3	Scent	reasonably well	strongly agree
4	Temperature	agree	Agree
5	Lighting	reasonably well	reasonably well
6	Colour	reasonably well	reasonably well

This study validates cleanliness with the previous studies (Hussain and Ali, 2015; Mathur and Goswami, 2014) and our finding is consistent with it. The study observed that cleanliness is given the second most utmost priority for the shopper, and it improves the atmosphere which affects the shoppers' good feeling towards the store. The following contributions are added to the body of knowledge: cleaning is the first impression to generate customer loyalty, i.e., when one place is filthy, the remainder of the location may be assumed filthy by the shopper, thus leading to bad experiences. Cleanliness impacts the whole process of shopping covering all clusters of shoppers and specifically, for nucleus and service vitality shopper the higher level of cleanliness leads to better effect.

This study validates scent with the previous studies (Mattila and Wirtz, 2001; Roschk *et al.*, 2017) and our finding is consistent with it. The study observed that scent enhances shopping outcomes. Once retailers incorporate environmental stimuli, smell is a vital factor. The following contributions are added to the body of knowledge are scent improves customer experience, increases dwell time, and willingness to purchase. Signature scents tap into certain memories and have a distinctive impact on the behaviour of the shopper and they come into contact with the store manager resulting in scent marketing.

The findings indicate the three imperative outcomes. First, retailers essentially to focus on three phases of shopper behaviour: entry, browsing, and exit. The first phase is entry wherein shoppers enter the store and cognitive computing based in-store analytics focus on measurement of the number of shoppers enters the store, time of the visit to judge a pattern in shopping behaviour, the direction the shoppers take when they enter the store. The second phase is browsing wherein shoppers shop/roam inside the store and cognitive computing based in-store analytics to focus on measurement of the conversion rate, average cart size, hot zones (shoppers spent most of the time), and cold zones (shoppers avoid the areas) in the store. The third phase is exit wherein shoppers exit the store and cognitive computing based in-store analytics to focus on measurement of immediate leavers, average time spent by the shopper, and most importantly average queue times while paying.

Second, to maintain a competitive edge in a fast-growing marketplace, retailers to look for proactive ways to harness new and comprehensive sources of data in distinctive ways. Cognitive computing based in-store analytics assist retailers to achieve actionable insights from shoppers' data and connect the dots between the shopper, the store, and the buying decision.

Third, one downside of retail atmospherics is the forceful use, which has the opposite impact by driving away prospective shoppers who prefer a more nuanced interaction with the store environment.

6.1. Theoretical contributions

This study yields major theoretical contributions. First, it established a personalised retail atmospherics model with the extension of Forrest's atmospherics model that identifies the rationale for "information need" as a component in the retail atmosphere, store performance as an add-on component, personalised shopper response and personalised shopper motivation and goals by encompassing insights on store performance and personalised shoppers.

Second, it is the first effort to consider AOV for store performance and remorse for personalised shopper behaviour in a retail atmospherics context. Knowing the AOV offers a window into shopper's behaviour which helps brick-and-mortar stores on the marketing effort and pricing strategy. Remorse offers a window to mend the relationship.

Third, it is the first effort to advance strategic marketing using SWOT analysis in a retail atmospherics context. Strategic marketing is the most effective way to reach personalised shoppers. Therefore, the study offers sufficient ground to demonstrate the atmospheric effects on brick-and-mortar store performance and personalised shopper's behaviour.

6.2. Practical implications

In emerging markets, organizational factors that promote a knowledge-supporting system fuel innovation (Zapata-Cantu, 2020), so the present research provides insights for marketers and executives who may be interested in taking advantage of in-store analytics and explains why attention should be paid to the cognitive computing solution to judge the influence of retail atmospherics on store performance and behaviour of personalised shoppers. However, the greatest promise of retail atmospheric will be realised by building a self-improving system, i.e., given a sufficient volume of data, it can better satisfy the need of the marketers and executives over time by answering analytical questions using descriptive, diagnostic, predictive, prescriptive, and cognitive analytics. The target of the analytics is primarily the shopper's current and anticipated behaviour in the store with a focus on optimizing store performance.

Small and medium scale retailers failed to understand the significance of atmospheric stimuli in identifying and distinguishing their brand from rivals. Such retailers should realise that individual atmospheric stimuli can be combined to produce the desired atmosphere to enhance sales rates, satisfy shopper's actual and emotional requirements, improve the degree of shopper involvement in a store, leading to good buying behaviour. For bigger retailers, external atmospheric stimuli are less important due to the reputation based on the products they sell, convenient places, and competitive prices.

6.3. Limitations and future research directions

Several interesting insights were offered by the research with the generalizability of the result. It does have a few constraints. First, a small set of data was considered for this study, and the primary data was collected from the brick-and-mortar store that was limited to the particular type of retailer. Second, the retailer attracts shoppers with discounts such as buy x items, get y items free, everyday low price, loyalty programs, free samples, so the study could not correctly define the correlation among (1) footfall count, conversation rate, UPT, AOV, dwell time, and (2) purchase intention, emotional experience, and remorse. Though, such correlations are beyond the purview of this study. Third, we put forward NPS, the diagnostic analytics text classification algorithm, and the extension of the personalisation in future works.

Net Promoter Score (NPS): It is a survey of the likelihood of a shopper recommending the product to a friend or colleague. The goal is to make the average NPS across all clusters of shoppers as high as possible. Brand loyalty is measured by NPS and represents the shopper's experience. To achieve this, the atmosphere of the store must be a place for an individual to feel comfortable hanging alone or with friends (Michelli, 2006). A higher score represents better shopper behaviour and a possible increase in in-store performance.

Hyper-personalisation: Hyper-personalisation's ultimate purpose is to boost the probability of business achievement by satisfying the shopper by gathering real-time behaviour data. One way of further improving the hyper-personalisation is to further classify (Behera *et al.*, 2020) the products based on cost and criticality, and unique selling proposition (i.e., USP).

Diagnostic analytics text classification algorithm: Text classification algorithm related to purchasing intention, emotional experience, and remorse i.e., the questions Q2 in Table AII of Appendix A (Why yours feeling while purchasing is positive or negative?), Q2 in Table AIII of Appendix **A** (Why your emotions while purchasing is positive or negative?), and Q3 in Table AIV of Appendix A (Why you feel shame or guilt while and after purchasing?). It is a form of advanced analytics to answer "why did it happen to the atmospheric feature". The algorithm can be characterized by the techniques of drill-down, data discovery, and correlations. Since, research and development operations are gradually located in emerging markets particularly in India by multinational corporations (Yip and McKern, 2014), the practitioner can conduct interview intensive research in emerging market like India to overcome any challenges.

7. Conclusion

The study outlined cognitive computing based in-store analytics to measure the influence of retail atmospherics on store performance and behaviour of personalised shoppers for a brick-and-mortar retailer by covering the atmospherics stimulus such as cleanliness, music, scent, temperature, lighting, and colour. The theoretical contribution named "Personalised Retail Atmospherics Model" was proposed, founded on "Forrest's Atmospherics Model". The proposed framework is composed of two building blocks, namely the shopper personalisation, and the in-store analytics platform based on cognitive computing. The data were collected from brick-and-mortar store based out in India, and a quantitative research method was conducted. The study revealed radical growth for cleanliness, scent feature and considerable growth was observed for music, temperature, lighting, and colour atmospheric stimuli. Personalisation will make the shopper feel that their mind has been read and the overall shopping experience in the shop will have a mammoth effect. Some small-scale brick-and-mortar stores failed to realise the atmospheric advantages of store performance and shopper satisfaction. Such businesses must appreciate the benefits in terms of the monetary performance of the store, market value and shopper value. Cognitive computing based in-store analytics' ultimate goal is to inform the brick-and-mortar retailers about what is working and what is not. Precisely, the research conduces to retail atmosphere in emerging market by presenting cognitive computing based in-store analytics.

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Appendix A

Table AI: Common questions for purchase intention, emotional experience, and remorse

Retail Atmospherics	Question
Cleanliness	Q1. The cleanliness in the store is fine.
	Q2. The floor's cleanliness of the store motivates me to buy more.
	Q3. The store's clean racks and stacks motivate me to stay longer.
	Q4. The store's cleanliness draws me to visit again.
Music	Q5. The music in the store is fine.
	Q6. Listening to music during shopping creates a relaxed atmosphere.
	Q7. Background music's presence improves my well-being and comfort.
	Q8. In-store music motivates me to purchase more.
	Q9. The background music volume makes me remain longer.
	Q10. Music developed a pleasant atmosphere that makes me spend more time in the shop.
Scent	Q11. The scent in the store is fine.
	Q12. The scent in the store encourages me to buy more.

	Q13. The scent in the store brings me back to the store.
	Q14. Store outlet fragrance makes me stay longer.
Temperature	Q15. The temperature in the store is fine.
	Q16. The air conditioning store's quality made my presence comfortable in the store
	Q17.The fully air-conditioned, shopping environment makes me comfortable.
	Q18.Without air conditioning, the store prevents me from shopping.
Lighting	Q19. The lighting in the store is fine.
	Q20. The store lighting is pleasing to the eyes, making me stay longer.
	Q21. Good lighting colour draws me to products.
	Q22.Store lighting makes products more visible and appealing to me.
	Q23. It is essential to see the distinct lighting used within the store in each region.
Colour	Q24. The store's colour is fine.
	Q25. In my mind, the colour of the store produces a favourable picture.
	Q26. The store's colour gives me a favourable perception.
	Q26. The store's colour gives me a favourable perception.

Table AII: Question for purchase intention

Questions for Purchase Intention
Q1. What do you feel while purchasing?
Q2. Why your feeling while purchasing is positive or negative?

Table AIII: Question for Emotional Experience

Questions for Emotional Experience
Q1. What are your emotions while purchasing and why?
Q2. Why your emotions while purchasing is positive or negative?

Table AIV: Question for Remorse

Questions for Remorse
Q1. Do you feel shame or guilt while and after purchase?
Q2. What are you feeling about shame or guilt while and after purchasing?
Q3. Why you feel shame or guilt while and after purchase?