Bridging the Attitude-Behaviour Gap in Biobased Product Consumption: A Comprehensive Behavioural Decision Model

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Abstract

Market acceptance of biobased products is essential for advancing a sustainable bioeconomy, yet consumer decision-making remains complex and insufficiently understood. This study introduces and validates the Comprehensive Behavioural Decision Model for Biobased Products (CBDM-BBP), designed to bridge the gap between consumer attitudes and actual use behaviour. The model integrates cognitive, affective, and conative dimensions while accounting for internal and external influences such as self-interest, altruism, and contextual factors. Using survey data from 525 consumers in the Republic of Ireland, a country with strong bioeconomy ambitions and policy support for biobased innovation, we applied Partial Least Squares Structural Equation Modelling (PLS-SEM) to evaluate the framework. Results demonstrate that CBDM-BBP outperforms individual theoretical models in explaining use behaviour, offering strong predictive capability. These findings suggest that consumer use behaviour of biobased products cannot be adequately explained through isolated behavioural

mechanisms but instead arises from the interaction of multiple psychological and contextual influences. The CBDM-BBP provides an empirically validated framework for capturing this complexity, offering a more comprehensive basis for understanding consumer behaviour in the bioeconomy.

Keywords

biobased products; bioeconomy transition; consumer behaviour; behavioural decision-making models; extended integrative behavioural framework

Table 1. Acronyms and abbreviations used throughout the study.

Acronym	Full term / Definition
ABC	Attitude-Behaviour-Context
AC	Awareness of Consequences
AR	Ascription of Responsibility
Att	Attitude
AVE	Average Variance Extracted
Awa	Awareness
BBPs	Biobased Products
CBDM-BBP	Comprehensive Behavioural Decision Model for Biobased Products
CVPAT	Cross-Validated Predictive Ability Test
$CVPAT^{IA}$	Naïve Indicator-Averages Prediction Benchmark
$CVPAT^{LM}$	Conservative Linear Model Prediction Benchmark
DoI	Diffusion Of Innovation Model
HoE	Hierarchy Of Effects Model
HTMT	Heterotrait–Monotrait Ratio
IA	Naïve Indicator-Averages
Intr	Interest
Intt	Intention
Know-Obj	Objective Knowledge
Know-Sub	Subjective Knowledge
LM	Conservative Linear Model
LV	Latent Variables
MAE	Mean Absolute Error
MV	Manifest Variables
NAT	Norm Activation Theory
NFI	Normed Fit Index
PA	Product Attributes
PB	Past Behaviour
PBC	Perceived Behavioural Control
Perc	Perception
PI	Policy Interventions
PLS-SEM	Partial Least Squares Structural Equation Modelling
PN	Personal Norms
R^2	Coefficient of Determination

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RMSE	Root Mean Square Error
SN	Social Norms
SRMR	Standardised Root Mean Square Residual
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
Tru	Trust
UB	Use Behaviour
VIF	Variance Inflation Factor
WTP	Willingness To Pay

1. Introduction

The bioeconomy is increasingly central to EU and global policy, driven by the promise of sustainable innovation (Sadeghzadeh et al., 2025). Its development hinges on new knowledge and technologies, yet this progress is accompanied by inherent risks and uncertainties (Dinu, 2019). As Pasnicu et al. (2019) note, transitioning to a bioeconomy requires not only embracing its principles but also crafting strategies grounded in thorough analysis.

This growing prominence has sparked scholarly interest in public acceptance, especially as national and regional strategies proliferate (Sadeghzadeh et al., 2025). Yet despite positive attitudes toward sustainability, consumer engagement with biobased products (BBPs) remains limited. Research highlights a persistent gap between intention and actual use (Behre & Cauberghe, 2024; Chang & Hung, 2023; Ketelsen et al., 2020; Park & Lin, 2020; Ruf et al., 2022). One contributing factor is that, compared to fossil-based alternatives, the environmental benefits of BBPs are not always visible to consumers (European Commission, 2025), which can hinder informed decision-making and adoption. This issue is further compounded by a lack of understanding regarding the factors that shape consumer behaviour (Nejadrezaei et al., 2024). For policymakers and managers, this presents a pressing challenge: how to foster meaningful acceptance of BBPs (Drabik & Wesseler, 2024).

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Addressing this challenge begins with conceptual clarity. The term "bioeconomy" lacks a universally accepted definition, reflecting diverse priorities across disciplines (Viaggi, 2017). The European Commission (2025) defines the bioeconomy as "the activities that deliver sustainable solutions based on biological resources to create added value." Within this context, BBPs are defined by the European Committee for Standardisation (CEN, 2014) as products wholly or partially derived from biomass of biological origin, such as plants, trees, or animals.

Understanding consumer engagement with BBPs requires insight into the psychological, sociological, and economic mechanisms that shape decision-making. Behavioural theories such as Ajzen's Theory of Planned Behaviour (TPB) and Schwartz's Norm Activation Theory (NAT) have long been used to explain pro-environmental actions (Ajzen, 1991; Harland et al., 2007; Klöckner & Blöbaum, 2010; Schwartz, 1977). However, given the complexity of sustainability challenges, scholars increasingly advocate for integrative models that synthesise multiple theoretical perspectives (Ajzen, 2020; Bamberg & Möser, 2007; Klöckner & Blöbaum, 2010).

In response, this study adopts an integrative approach to better capture the multifaceted nature of consumer behaviour. The objective of this study is to develop and validate a comprehensive behavioural framework for biobased products that captures the consumer decision-making journey from initial awareness to actual product use. The originality of the proposed approach lies in integrating cognitive, affective, and conative dimensions with self-interest, altruistic, and contextual influences within a single framework. This integrated perspective addresses the fragmented nature of existing behavioural approaches and provides a more comprehensive basis for examining consumer use behaviour of biobased products.

The remainder of the paper is organised as follows. The next section develops the integrated framework by presenting the rationale for theory integration, introducing the CBDM-BBP, and

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discussing the behavioural constructs, assumptions, and additional factors incorporated into the framework. Subsequent sections describe the research methodology, present the results, discuss the findings, and conclude the paper.

2. Toward an Integrated Framework

2.1. Rationale for Theory Integration

Theory integration provides a robust solution to the limitations of individual models by consolidating overlapping constructs and incorporating additional variables and processes, thereby enhancing predictive capability while maintaining a coherent theoretical foundation (Hagger & Hamilton, 2020). Hagger and Hamilton (2020) further note that integrated theory-based interventions remain relatively sparse, particularly studies examining how changes in distinct constructs influence behaviour.

This integrative perspective is especially relevant to biobased products, where consumer decisions are shaped by a complex interplay of environmental, economic, social, ethical, and political factors (Nejadrezaei et al., 2024). Existing frameworks often address these dimensions in isolation, resulting in fragmented or incomplete insights (Halder et al., 2016; Wensing et al., 2021). By unifying these elements, an integrated approach provides a holistic understanding of the drivers and barriers influencing consumer engagement, supports more informed decision-making, advances academic knowledge, and equips policymakers, managers, and practitioners with practical tools for designing interventions that align with consumer values and promote sustainable consumption.

2.2. Introducing CBDM-BBP

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111 Building on the rationale for theory integration, the present study introduces the
112 Comprehensive Behavioural Decision Model for Biobased Products (CBDM-BBP), a
113 theoretical framework designed to deepen understanding of consumer decision-making in the
114 context of biobased products. By integrating multiple theoretical perspectives, the CBDM-BBP
115 addresses the limitations of single-theory models and captures the complex interplay of
116 cognitive, normative, and contextual factors influencing consumer behaviour.

117 The model builds on the framework on biobased products proposed by Nejadrezaei et al.
118 (2024), integrating Rogers' (2003) Diffusion of Innovation Model (DoI) and Lavidge and
119 Steiner's (1961) Hierarchy of Effects Model (HoE)[1] (see Fig. 1). It further combines cognitive
120 and normative theories with internal and external influences to better reflect the complexities
121 of real-world decision-making. External influences are particularly relevant in the context of
122 biobased products and packaging, where consumers evaluate a range of product attributes,
123 including search, experience, and credence attributes, alongside environmental considerations.
124 These attributes encompass characteristics that can be assessed before purchase, through use,
125 or only after consumption, and therefore shape consumer expectations, evaluations, and
126 adoption decisions. Additionally, the model acknowledges the role of policy instruments,
127 including information-based measures, market-based incentives, regulatory approaches, and
128 behavioural nudges, in shaping market conditions and consumer behaviour, thereby
129 influencing the decision-making process and the diffusion of biobased alternatives. The model
130 conceptualises behaviour across three key levels, structured into eight interactive decision-

[1] Lavidge and Steiner (1961) suggest that consumers do not instantly transition from indifference to committed purchasing. Similarly, Rogers (2003) asserts that individuals adopt innovations through a gradual decision-making process. While these models provide insights into consumer behaviour, they assume a rational, step-by-step progression, overlooking other influential factors and the diverse ways they shape decision-making.

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making stages, offering a nuanced and dynamic view of consumer engagement with biobased products (see Fig. 1).

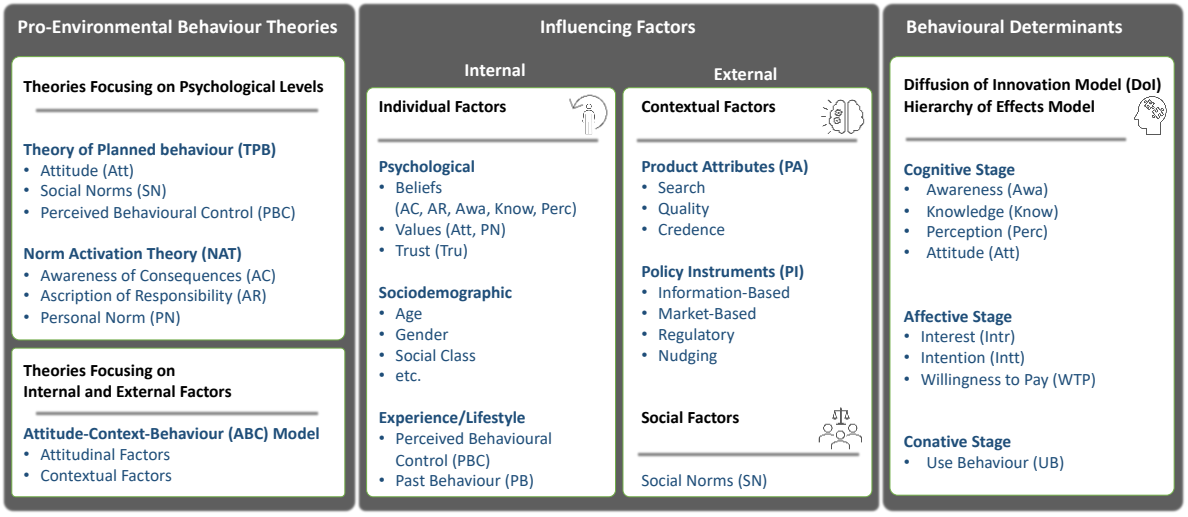


Figure 1. General conceptual foundation of the CBDM-BBP, illustrating the key dimensions and influences underlying consumer decision-making for biobased products.

2.3. Behavioural Constructs and Assumptions

2.3.1. Addressing the Behaviour Gap

Following Nejadrezaei et al. (2024), the first key assumption in the CBDM-BBP is that acceptance precedes actual use. Increased consumer interest in biobased products will enhance intentions to use, raise willingness to pay premiums and lead to greater actual use. Furthermore, those with stronger intentions are likely to be more willing to pay and use. While this is a novel approach to exploring these determinants in greater depth, previous empirical studies on biobased fields have already examined the link between intention and use (Sajincic et al., 2021; Stahl et al., 2021), such as those based on the Theory of Reasoned Action (TRA) and TPB. Thus, instead of having only intention and use behaviour, the behavioural determinants include interest, intention, willingness to pay, and actual use behaviour (see Fig. 1), providing a better understanding of consumer decision-making.

2.3.2. Limitations of TPB and NAT

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149 The CBDM-BBP builds on the theoretical foundations of the TPB and NAT, which are widely
150 recognised for explaining pro-environmental behaviour. However, the TPB has been criticised
151 for its firm reliance on rational cost-benefit analyses, often overlooking altruistic and non-
152 rational motivations that shape actual behaviour, raising concerns about its validity in pro-
153 social contexts (Joshi & Rahman, 2015; Vermeir & Verbeke, 2008; Wheale & Hinton, 2007;
154 Zemo & Termansen, 2021). Similarly, the NAT exhibits limited capacity to account for
155 involuntary or self-interest-driven behaviours, which reduces its predictive power in many
156 contexts (Esfandiar et al., 2020; Rezaei et al., 2019).

157 **2.3.3. Addressing Limitations through an Integrative Approach**

158 As highlighted by Bamberg and Möser (2007) and further emphasised by Nejadrezaei et al.
159 (2024) in the context of consumer perspectives on biobased products, pro-environmental
160 behaviour is most effectively understood as a mix of self-interest and pro-social motivations.
161 This perspective suggests that relying solely on a single theoretical lens, whether rational or
162 pro-social, may be insufficient to fully capture the complexities of consumer behaviour related
163 to biobased products, highlighting the need for integrative approaches. Such integration has
164 been observed in various empirical studies beyond biobased products (Esfandiar et al., 2021;
165 Nascimento & Maria Correia Loureiro, 2024; Safa & Mohammadian Saghinsara, 2020;
166 Setiawan et al., 2020; Wall et al., 2007; Zhang et al., 2017).

167 **2.3.4. Relationships Between Constructs**

168 Aligned with Ajzen's (2020) suggestion to include more predictors in the TPB, the CBDM-
169 BBP enhances our understanding of consumer behaviour related to biobased products. This
170 approach integrates the TPB, a cognitive behavioural theory, with elements of the NAT, which
171 emphasises normative influence on behaviour. While the TPB identifies attitude and social
172 norms as the immediate determinants of behaviour, the NAT focuses on personal norms.

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The CBDM-BBP goes further into the relationships between the construct and behavioural determinants in the established models. Building on previous research indicating a positive relationship between personal norms and attitudes (Arundati et al., 2020; De Pelsmacker & Janssens, 2007; Guan & Zhang, 2023), as well as studies linking social norms to attitudes (Halder, 2016; Halder et al., 2016), we posit that consumers influenced by social and moral considerations are more likely to develop favourable attitudes toward biobased products (see Fig. 2). Additionally, based on the work of Kim and Seock (2019); Onwezen et al. (2013); Rezaei et al. (2019) on the relationships between SN and PN, we assume that socially influenced consumers are more likely to develop more favourable attitudes toward biobased products (see Fig. 2).

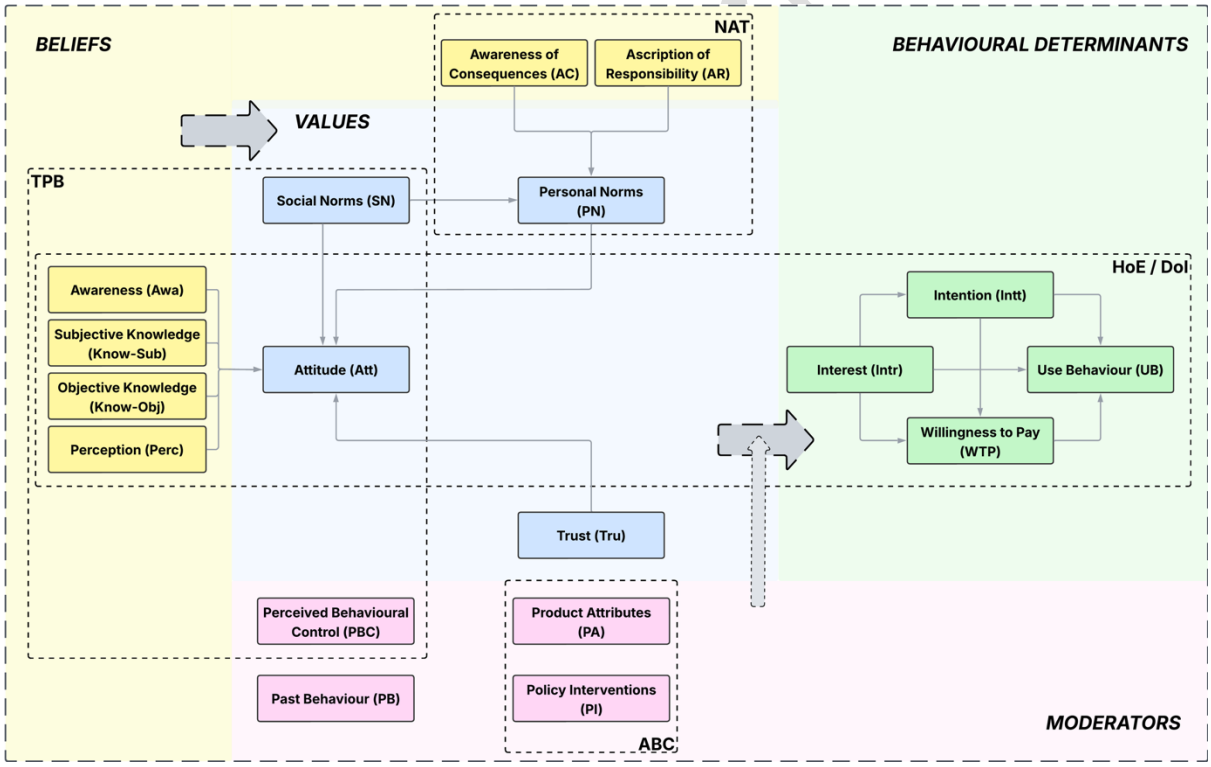


Figure 2. Figure 2. Conceptual framework of the CBDM-BBP, showing the integration of constructs from TPB, NAT, ABC, HoE, and DoI and their relationships within the proposed model.

In this study, we also expect that individuals' beliefs shape their values directly and behavioural determinants indirectly through values (see Fig. 2). Building on previous studies (Carfora et

al., 2020; Fallah Zavareh et al., 2020; Rezaei et al., 2019; Savari et al., 2023) including those in biobased products (Ataei et al., 2022; Constantine et al., 2020; Wensing et al., 2021; Zhang et al., 2018), we assume that consumers who understand the consequences of conventional products (AC) and feel a greater sense of responsibility for their negative impacts (AR) will exhibit stronger moral values and higher behavioural determinants towards biobased products. Drawing on previous research (Guo et al., 2021; Halder et al., 2012; Sajincic et al., 2021), we assume that consumers with greater awareness, perception, and subjective (Know-Sub) and objective knowledge (Know-Obj) are likely to have more favourable attitudes, which in turn strengthen behavioural determinants (see Fig. 2).

The TPB highlights perceived behavioural control (PBC) as a key predictor of intentions and behaviours, particularly when actions are not entirely under individual volition (Chaudhary & Bisai, 2018). PBC reflects individuals' perceived ability to perform a behaviour, shaped by experiences, obstacles, and resources (Ajzen, 1991, 2020). Findings in consumer research, including biobased products, are mixed: some link high PBC to positive behavioural outcomes, while others find little effect (Halder, 2016; Halder et al., 2016; Notaro, Paletto, et al., 2022). Theoretically, PBC moderates the impact of attitude, subjective norms, and intention on behaviour (Ajzen, 2020; La Barbera & Ajzen, 2020, 2021). In the context of biobased products, perceived control over factors such as convenience, availability, and price may moderate the relationships between values, trust, and behavioural determinants (Filho et al., 2022; Ladu et al., 2019; Notaro, Lovera, et al., 2022).

2.4. Incorporating Additional Factors

In addition to the theoretical foundations, these theories face difficulties in accurately predicting individual behaviour, particularly concerning trust, past behaviour, and contextual factors.

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2.4.1. Contextual Factors: The ABC Model

The CBDM-BBP follows Stern's (2000) Attitude-Behaviour-Context (ABC) theory. Incorporating the ABC model into the integrated framework also helps address the limitations of the DoI and HoE models, whose linear structure and assumption of purely rational behaviour fail to account for other influencing factors and their impact on decision-making (Barry & Howard, 1990; Chakravarty & Sarma, 2022; MacVaugh & Schiavone, 2010). Stern (2000) further argues that pro-environmental actions result from a complex interaction between external factors and individual characteristics, a perspective also discussed by Guagnano et al. (1995). This approach is particularly relevant given the limitations of the TPB and NAT in predicting individual behaviour in the context of biobased products, notably their insufficient consideration of contextual influences.

The ABC model posits that pro-environmental actions emerge from a multifaceted interaction between individual and external elements (Salonen & Åhlberg, 2012; Shove, 2010; Stern, 2000; Xu et al., 2017) (see Fig. 1). While individual factors encompass personal beliefs, values, and perceptions of the benefits and drawbacks of specific behaviours, contextual variables, which can either facilitate or constrain actions, include aspects such as convenience, financial incentives, costs, physical abilities, institutional and legal frameworks, public policy support, and societal norms and expectations (Stern, 2000).

Previous studies have highlighted the direct effects of external factors such as product attributes and policy interventions on consumer perspectives and behavioural determinants (Friedrich, 2022; Gaffey et al., 2021; Klein et al., 2020; Scherer et al., 2018). Building on Nejadrezaei et al. (2024), this study instead examines how these external factors interact with individual-level variables, assuming they moderate the relationships between values, trust, and behavioural determinants by strengthening, weakening, or reversing their effects (see Fig. 2).

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Within this contextual group, product attributes, defined as characteristics that consumers can evaluate before or after purchase (Andersen & Philipsen, 1998; Krouse, 1990), were introduced by Nejadrezaei et al. (2024) to assess consumer evaluations of biobased products. These attributes are classified as search, experience, or credence attributes (Andersen & Philipsen, 1998; Darby & Karni, 1973; Nelson, 1970), reflecting both tangible and intangible elements that shape decision-making before and after consumption (Pizzutti et al., 2022). In the same study, policy instruments were defined as mechanisms through which governments steer social change (Bemelmans-Videc et al., 2017), categorised into four types: information-based instruments, market-based (fiscal) measures, regulatory instruments, and behavioural nudges.

2.4.2. Individual Factors: Trust and Past Behaviour

As noted by Filimonau et al. (2018) and Van de Velde et al. (2009), the market acceptance of emerging innovations heavily depends on consumer trust. In psychology, trust is considered a behavioural intention or internal action, akin to choice, judgment, or preference (Davydenko et al., 2018). López-Mosquera et al. (2015) identified trust as a key element in fostering pro-environmental behaviour that supports environmental enhancement. While biobased products have existed in the European market for over a decade, newer applications and product categories continue to emerge, and consumer understanding remains uneven. This can contribute to scepticism (Fernández et al., 2023), particularly due to uncertainties about product attributes and perceived risks.

Accordingly, another assumption within the individual factors is that consumers with higher levels of trust are likely to exhibit more favourable attitudes and stronger behavioural determinants (see Fig. 2). The influence of trust on consumer behaviour has been extensively studied across various disciplines, including biobased products (Dessi et al., 2022; Harring et al., 2019; Liao & Xing, 2023; Meeusen et al., 2015; Nyangau et al., 2022). According to

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Nguyen et al. (2021), trust is crucial for reducing perceived risks and increasing expectations regarding biobased products. Additionally, prior studies highlight its positive influence on attitudes, intentions, and behavioural support (Butkowski et al., 2020; Nguyen et al., 2021)

In addition to trust, positive experiences can encourage repeat purchases and foster customer loyalty, whereas negative experiences may discourage individuals from purchasing the same or related products in the future. Past behaviour (PB), as an indicator of habit strength, is a critical construct in the TPB and has been a subject of intense discussion in the literature (Ajzen, 2020; Sommer, 2011). Its influence on consumer decisions is significant, as it affects the extent of deliberative processing during decision-making (Kidwell & Jewell, 2008). In the context of biobased products, the literature suggests that positive individual experiences shape consumer knowledge, perceptions, and attitudes (Al-Hassan et al., 2010; Klein et al., 2019). Therefore, as recommended by Nejadrezaei et al. (2024), we assume that individuals' prior experiences with biobased products (as a moderator) influence the strength and direction of the associations between their values, trust, and behavioural determinants (see Fig. 2).

3. Materials and Methods

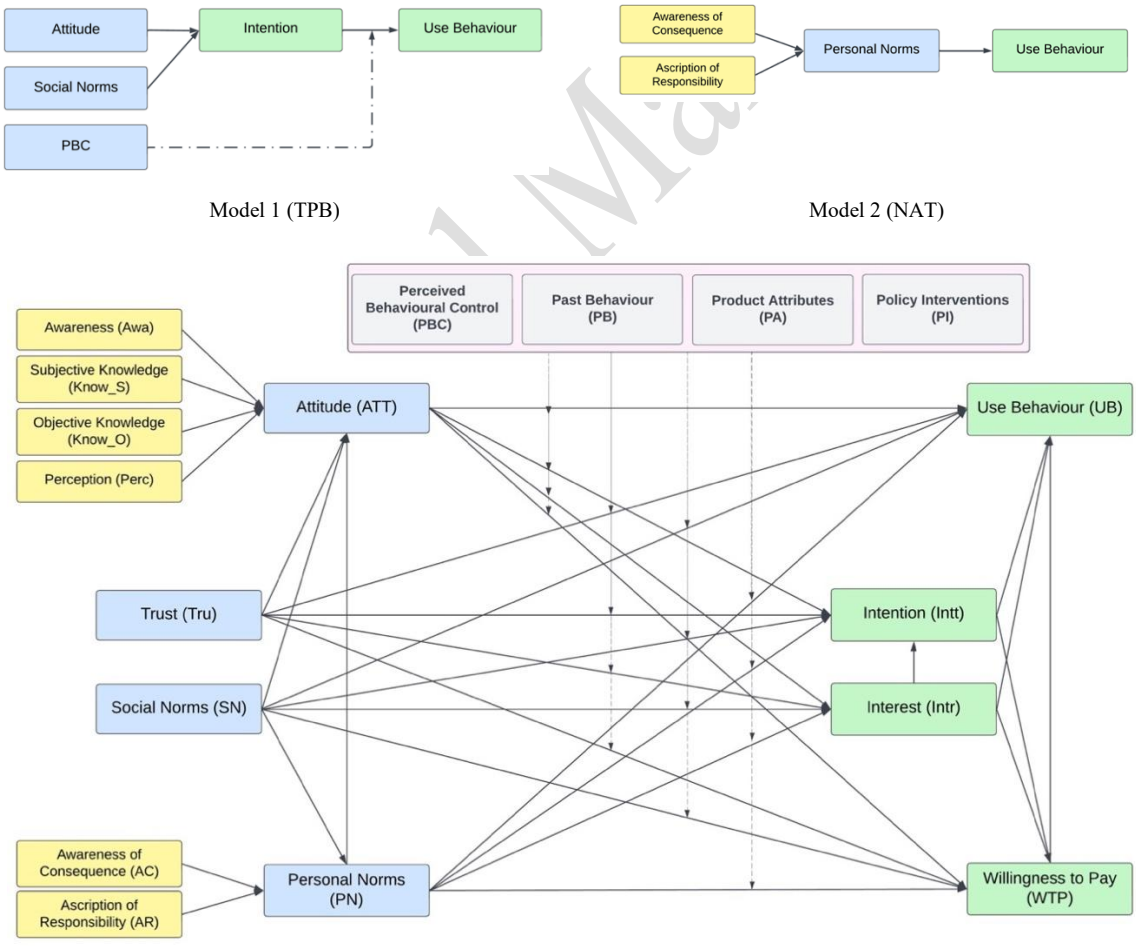
3.1. The Present Study

To address concerns about the limited predictive capability in management and social science research, Liengaard et al. (2021) recommend methodologies that combine explanatory modelling with predictive assessment. Partial Least Squares Structural Equation Modelling (PLS-SEM) offers such an approach, making it a valuable method for investigating consumer behaviour (Kurtaliqi et al., 2024) and an essential tool in marketing research (Sarstedt et al., 2022). It is widely recognised for its ability to compare alternative conceptual models (Richter & Tudoran, 2024) and to generate theories that both explain and predict outcomes effectively (Hair & Sarstedt, 2021; Liengaard et al., 2021; Sarstedt & Danks, 2022). By integrating

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explanation and prediction, PLS-SEM enhances understanding of theoretical constructs and their relationships while maintaining predictive accuracy (Liengaard et al., 2021; Sharma et al., 2022).

This study employs PLS-SEM to evaluate three model configurations: the TPB and NAT as established, less complex frameworks, and the CBDM-BBP as an integrated alternative, with a focus on use behaviour (UB) as the key construct (see Fig. 3). Model 1 represents the TPB (Ajzen, 1991), Model 2 the NAT mediator model (Schwartz, 1977), and Model 3 (CBDM-BBP) extends these by integrating their constructs to capture more complex consumer decision-making processes.



Model 1 (TPB)

Model 2 (NAT)

Model 3 (CBDM-BBP)

Figure 3. Comparison of the TPB, NAT, and the proposed CBDM-BBP, illustrating the constructs and relationships used to explain consumer use behaviour of biobased products.

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In line with Sharma (2019; 2021), model development strikes a balance between complexity and parsimony. Complex models capture the multidimensional nature of consumer behaviour but risk overfitting and reduced interpretability, while parsimonious models enhance clarity and generalisability but may omit relevant constructs. The integrated model (Model 3) was therefore designed to reflect the multidimensional nature of consumer behaviour toward biobased products while remaining theoretically grounded and empirically parsimonious (Ajzen, 2020; Fishbein & Ajzen, 2011). Evaluation followed Sharma's (2019) five-step procedure, ensuring coherence, predictive power, and statistical rigour.

3.2. Measurement

This study employed a quantitative research design, utilising a structured survey method to empirically test the CBDM-BBP. An online questionnaire was administered with the assistance of a market research agency (Behaviour and Attitude). Prior to participation, respondents were provided with brief and neutral information about the study and informed that participation was entirely voluntary and responses would remain confidential. Participants received a general definition of biobased products to establish a common baseline understanding. However, they were not presented with detailed information regarding specific material properties, functional performance characteristics, quantified environmental impacts, or comparative advantages relative to conventional alternatives.

Consequently, responses reflect evaluations of the general concept of biobased products rather than reactions to a defined set of product characteristics. Furthermore, while use behaviour was measured using several examples of biobased packaging applications, including coffee capsules, fruit and vegetable packaging, meat trays, and bottles for detergents and personal care products, respondents were not restricted to a single product category or use context. This

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318 approach was intended to support the development of a broadly applicable behavioural
319 framework.

320 The instrument comprises 18 constructs (Latent Variables), measured using 90 indicators
321 (Manifest Variables) related to bioplastics application in packaging (see Appendix A). Each
322 indicator, except those assessing objective knowledge and past behaviour, was rated on a 5-
323 point Likert scale. The measurement items were derived from established frameworks and prior
324 empirical studies. Several indicators were adapted from validated scales (Ajzen, 2006; De
325 Groot & Steg, 2009; Klöckner & Blöbaum, 2010), while context-specific constructs, including
326 trust, were operationalised using reformulated items based on prior research (Filho et al., 2022;
327 Filimonau et al., 2018; Le-Anh & Nguyen-To, 2020; Magnier et al., 2019; Onwezen et al.,
328 2013). This approach ensured both theoretical grounding and contextual relevance, consistent
329 with the recommendations of Ajzen (2020) and Fishbein and Ajzen (2011).

330 A pre-test was conducted to establish face and content validity, following the guidelines of
331 Diamantopoulos et al. (2012). Subsequently, a pilot study involving 55 participants was carried
332 out to evaluate reliability (Sim & Lewis, 2012). All constructs demonstrated acceptable
333 reliability, with Cronbach's alpha values exceeding the 0.7 threshold. Two constructs scored
334 slightly below at 0.67, which is still considered suitable for exploratory research (Sim & Lewis,
335 2012).

336 Following data collection, the measurement model was evaluated using standard PLS-SEM
337 procedures, including assessments of internal consistency reliability, convergent validity, and
338 discriminant validity, as described in the following sections.

339 **3.3. Sampling**

340 The conceptual framework underpinning this study is grounded in prior literature examining
341 environmental behaviour at the European and broader international levels. As such, the

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proposed relationships are not context-specific but theoretically applicable across diverse settings. Empirically, the study focuses on consumers in the Republic of Ireland. The conceptual framework underpinning this study is grounded in prior literature examining environmental behaviour at the European and broader international levels. As such, the proposed relationships are not context-specific but theoretically applicable across diverse settings. Empirically, the study focuses on consumers in the Republic of Ireland. Ireland was selected as the empirical setting due to its strong policy commitment to the bioeconomy and sustainable consumption, reflected in the Government's ambition to become a global leader in the bioeconomy and its active promotion of biobased products as drivers of sustainable transition (Government of Ireland, 2018, 2022a, 2022b, 2023). Furthermore, Ireland's natural resource base and ongoing investments in bioeconomy research and innovation make it a relevant context for examining consumer behaviour towards biobased products (Devaney & Henchion, 2017). Accordingly, the study focused on adult consumers residing in the Republic of Ireland (N = 3,930,572). To determine the appropriate sample size, we applied the inverse square root method proposed by Kock and Hadaya (2018) (Eq. 1), which indicated a minimum required sample of 491 to ensure sufficient statistical power at the 1% significance level.

$$Significance\ level = 1\%: n_{min} > \left(\frac{3.168}{|p_{min}|}\right)^2 = \left(\frac{3.168}{0.143}\right)^2 = 490.7 \quad (1)$$

where n_{min} denotes the minimum required sample size, and p_{min} represents the smallest path coefficient in the PLS model expected to be statistically significant, assuming significance levels of 1% (3.168), 5% (2.486), and 10% (2.123).

In this study, quota sampling techniques combined with convenience sampling from an online panel were employed through a market research agency (Behaviour and Attitude) to recruit participants, ensuring proportional representation across key demographic factors, including age, gender, region, and social class. Following the application of quality control measures,

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525 valid responses were retained for analysis. As shown in Table B.1 (Appendix B), the sample closely aligns with the national demographic profile (CSO, 2022).

3.4. Data Analysis

This study applied PLS-SEM, chosen for its suitability in evaluating the robustness of complex models, as well as its capacity to assess both explanatory and predictive power (Hair et al., 2022; Hair et al., 2011). The evaluation followed a two-step approach, beginning with the assessment of the measurement model and subsequently the structural model (Hair et al., 2022; Henseler et al., 2015; Ringle et al., 2023). In addition, the study examined the explanatory and predictive capabilities of the proposed model (Hair et al., 2022; Liengaard et al., 2021; Ringle et al., 2023; Ringle et al., 2024; Sharma et al., 2022; Shmueli et al., 2019). All analyses were conducted using SmartPLS$_4$ (Ringle et al., 2024) to estimate model parameters.

To ensure that the CBDM-BBP model met established measurement and structural quality standards, reliability and validity were assessed using conventional criteria. For reflective measurement models, indicator reliability was evaluated using a threshold of ≥ 0.708, internal consistency reliability was assessed via rho$_A$ values ranging between 0.70 and 0.90, and convergent validity was examined using the average variance extracted (AVE) with a minimum threshold of 0.50. Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT), with values below 0.90 considered acceptable (Hair et al., 2022; Henseler et al., 2015; Ringle et al., 2023). For formative measurement models, convergent validity was assessed through redundancy analysis, with values exceeding 0.708 indicating adequacy (Hair et al., 2022; Ringle et al., 2023). Multicollinearity was examined for both inner and outer models using the variance inflation factor (VIF), ensuring values did not exceed the threshold of 5 (Hair et al., 2022).

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Regarding the structural model, although hypothesis testing was not the primary focus of this study, statistical significance was assessed using the bootstrapping procedure recommended by Hair et al. (2022). A total of 5,000 subsamples were generated to evaluate the significance of path coefficients across the proposed research models (Models 1-3).

Model fit was evaluated using the standardised root mean square residual (SRMR), with values below 0.08 indicating acceptable fit (Hair et al., 2022; Hu & Bentler, 1998). Additionally, the normed fit index (NFI) was considered, while acknowledging that values may not necessarily reach the 0.90 benchmark suggested by Ringle et al. (2024).

From an explanatory perspective, the study examined how well the competing models fit the observed data (in-sample data) using in-sample evaluation metrics. In line with the guidelines of Sharma et al. (2022) and Hair et al. (2022), explanatory power was assessed through the coefficient of determination (R^2) alongside model fit indices. Following Shmueli (2010) and Hair et al. (2022), validating PLS-SEM results should emphasise generalisability-specifically, the model's ability to predict both in-sample and out-of-sample data. Therefore, the predictive assessment shifted the focus in-sample evaluation to the model's ability to accurately predict unseen data. This out-of-sample predictive evaluation employed the $PLS_{Predict}$ procedure (Shmueli et al., 2016) and the cross-validated predictive ability test (CVPAT) (Liengaard et al., 2021).

Predictive performance was assessed at both the indicator level and the construct level (use behaviour) using $PLS_{Predict}$ and CVPAT. The analysis applied a 10-fold cross-validation procedure with 10 repetitions, following recommendations by Witten et al. (2017), as cited in Hair et al. (2022). Within $PLS_{Predict}$ predictive relevance was evaluated using the $Q^2_{Predict}$ statistic at both the manifest and latent variable levels. Positive $Q^2_{Predict}$ values indicate

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413 predictive relevance, whereas values equal to or below zero suggest a lack of predictive
414 capability (Hair et al., 2022).

415 Prediction errors were assessed using the root mean square error (RMSE), or alternatively the
416 mean absolute error (MAE) in cases of highly skewed error distributions (Hair et al., 2022;
417 Ringle et al., 2023; Shmueli et al., 2019). Furthermore, the models were compared against
418 benchmark prediction approaches, including a naïve indicator-averages (IA) model and a
419 conservative linear model (LM), using CVPAT at both the overall model level and for the
420 specific construct of use behaviour (Sharma et al., 2022). After establishing predictive validity
421 across all models, the performance of Model 3 was compared with the baseline models (Models
422 1 and 2) to determine its relative predictive superiority.

423 **4. Results**

424 **4.1. Measurement Model Assessment**

425 The measurement model results indicate that the reflective constructs (outer model)
426 demonstrated satisfactory reliability and validity, as evidenced by indicator reliability, internal
427 consistency reliability, convergent validity, and discriminant validity (see Tables B.2 and B.3,
428 Appendix B). These findings confirm that the measurement items adequately represent their
429 respective constructs, exhibit internal consistency, correlate appropriately with related
430 measures, and remain empirically distinct from one another.

431 Regarding the formative measurement model (inner model), the results of the redundancy
432 analysis support its convergent validity (see Table B.4, Appendix B). Furthermore, as reported
433 in Tables B.4 and B.5 (Appendix B), multicollinearity was not detected in either the outer or
434 inner models, as all VIF values remained below the recommended threshold of 5.

435 **4.2. Structural Model Assessment**

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436 The bootstrapping outcomes for Model 1 indicate that nearly all path coefficients are
437 statistically significant for their respective relationships, except for the moderating effect of
438 PBC on the relationships between intention and use behaviour. Similarly, Model 2 reveals that
439 all path coefficients are statistically significant for their relationships (see Table B.6 in
440 Appendix B). In Model 3, most direct path coefficients are statistically significant, indicating
441 strong relationships between the variables.

442 The results demonstrate a significant influence of earlier behavioural determinants on later
443 ones, progressing from interest to intention, willingness to pay, and use behaviour. The size
444 and effect of values and trust vary among the behavioural determinants. Attitude significantly
445 influences all behavioural determinants. The effects on interest (.435***) and intention (.103*)
446 were positive, whereas the effects on willingness to pay (-.118*) and use behaviour (-.121*)
447 were negative. In contrast trust (Intr: .146***, Intt: .125**) and personal norms (Intr: .286***,
448 Intt: .139**, WTP: .246***) primarily affect the early stages, whereas social norms influence
449 later stages (WTP: .228***, UB: .288***). Trust and personal norms both had a significant effect
450 on attitude (.188**, .336***). Social norms had a significant positive effect on personal norms
451 (.533***), whereas their effect on attitude was not statistically significant (.188^{ns}) (see
452 Table B.6, Appendix B).

453 The CBDM-BBP reveals several statistically significant moderation effects, including those
454 related to PBC (e.g., PBC x PN->UB: .210**), product attributes (e.g., PA x Tru->Intt: .173**),
455 and policy instruments (e.g., PI x PN->Intt: .156*). However, several moderating relationships
456 in the structural model were not statistically significant (see Table B.6, Appendix B). These
457 paths were retained in the model in line with recommendations by Hair et al. (2022) and Sharma
458 et al. (2022), who suggest that non-significant effects may reflect context-specific dynamics
459 rather than model misspecification.

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4.3. Model Comparison Results

Regarding explanatory power, the results indicate that the R^2 values of all three models meet Cohen's (1988) threshold for substantial effect and Ozili's (2023) criterion for acceptability in social science research. The proportion of variance explained in use behaviour is highest for Model 3 (26%), followed by Model 1 (15%) and Model 2 (9%) (see Table 2). This improvement aligns with the integrative nature of Model 3, which incorporates a broader set of theoretically relevant constructs, including trust, that are not explicitly represented in Models 1 (TPB) and 2 (NAT). Compared to these models, Model 3 captures additional value-driven and trust-based mechanisms, which appear particularly influential in the early stages of behavioural formation (e.g., interest and intention). The findings suggest that trust and value-based factors strengthen the progression from initial interest to actual use behaviour by capturing both cognitive and normative drivers of decision-making. This highlights the importance of integrating rational and normative dimensions to provide a more comprehensive theoretical explanation of biobased product use behaviour (see Table B.6, Appendix B).

Table 2. Comparison of explanatory power and model fit criteria across the TPB, NAT, and CBDM-BBP model configurations.

Explanatory Power	Criteria	Model (1) TPB	Model (2) NAT	Model (3) CBDM-BBP
Explained Variance	R^2	.155	.093	**.266**
	R^2_{adj}	.150	.091	**.226**
Model Fit (Estimated)	SRMR	**.077**	**.057**	**.074**
	NFI	.847	.898	.785

Bold values represent best value

In terms of model fit, all three models exhibit acceptable performance. The SRMR values fall below the recommended threshold of 0.08 (Hair et al., 2022; Hu & Bentler, 1998), indicating satisfactory model fit. However, the NFI values do not reach the 0.90 benchmark suggested by

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Ringle et al. (2024). This limitation reflects a known constraint of PLS-SEM in assessing overall model fit. As highlighted by Hair et al. (2022), PLS-SEM is primarily prediction-oriented (as discussed in the following section) rather than designed for covariance-based model fit evaluation, and therefore requires alternative model assessment criteria.

The $PLS_{Predict}$ results revealed positive $Q^2_{Predict}$ values for all use behaviour indicators (UB1-UB5) across the three models (see Table 3), indicating that the PLS path model achieves lower prediction error than the naïve benchmark and thus exhibits predictive relevance (Hair et al., 2022). A comparison of RMSE and MAE values from the PLS-SEM models with those obtained from the LM for each indicator of the target construct use behaviour indicates that Model 3 demonstrates the strongest predictive performance (see Table 3). Specifically, Model 3 produced lower prediction errors for four out of five indicators compared to the LM, suggesting higher predictive capability (Ringle et al., 2023; Shmueli et al., 2019). At the construct level, Model 3 also yielded lower RMSE and MAE values than Models 1 and 2, further confirming its superior predictive power (Hair et al., 2022).

Table 3. Comparison of predictive performance criteria across the TPB, NAT, and CBDM-BBP model configurations.

Predictive Power			**Model (1) TPB**	**Model (2) NAT**	**Model (3) CBDM-BBP**
$PLS_{Predict}$					
MV^2	$Q^2_{Predict}$	UB 1	.065	.021	**.069**
		UB 2	.062	.039	**.076**
		UB 3	.065	.022	**.083**
		UB 4	.079	.017	**.085**
		UB 5	.091	.019	**.105**
	RMSE	UB1-5	0/5	3/5	**4/5**
	MAE	UB1-5	1/5	**4/5**	**4/5**
LV^3	$Q^2_{Predict}$	UB	.122	.041	**.141**

[2] Manifest Variables (Constructs)
[3] Latent Variables (Indicators)

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	RMSE	UB	.942	.985	**.932**
	MAE	UB	.706	.726	**.699**
CVPAT					
IA[4]	PLS loss- IA loss	Construct	-.077, .000***	-.025, .018*	**-.089, .002***
		Overall	-.180, .000***	-.111, .000***	**-.280, .000***
LM[5]	PLS loss- LM loss	Construct	.031, .114ns	.002, .867ns	**-.052, .018***
		Overall	.013, .292ns	.000, .973ns	**-.028, .001****

Bold values represent best value; ns: Not Significant

* 95% confidence level (.05 sig level); ** 99% confidence level (.01 sig level); *** 99.9% confidence level (.001 sig level)

The initial CVPAT results indicate that all models exhibit significantly lower average prediction loss (i.e., higher predictive accuracy) compared to the IA benchmark, thereby satisfying the minimum criteria for predictive validity (Sharma et al., 2022). However, as shown in Table 3, the $CVPAT^{IA}_{Overall}$ and $CVPAT^{IA}_{Construct}$ results reveal that Model 3 achieves lower average losses both at the overall model level (across all endogenous variables: - 0.280**) and for the target construct use behaviour (- 0.089***) compared to Models 1 and 2. These findings suggest that Model 3 exhibits lower PLS prediction loss at both the construct and overall levels, indicating significantly stronger predictive validity.

As shown in Table 3, the conservative LM benchmark results from the CVPAT ($CVPAT^{LM}$) indicate that Models 1 and 2 do not achieve significantly lower average prediction loss compared to the LM benchmark, as the differences at both the use behaviour construct level and the overall model level are not statistically significant. In contrast, Model 3 exhibits significantly lower average prediction loss than the LM benchmark at both levels (- 0.052*, - 0.028**), indicating stronger predictive performance. These findings suggest that the CBDM-BBP (Model 3) is the only model meeting the criteria for strong predictive validity relative to the LM benchmark (Sharma et al., 2022). Therefore, based on the CVPAT results, the CBDM-

[4] Naïve Indicator-Averages Prediction Benchmark

[5] Conservative Linear Model Prediction Benchmark

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512 BBP model demonstrates superior predictive accuracy in explaining biobased product use
513 behaviour compared to the TPB and NAT models.

514 The following sections discuss these findings, considering existing literature, and explore their
515 implications for theory, practice, and future research.

516 **5. Discussion**

517 **5.1 Model performance**

518 This study evaluated the robustness of the proposed model using two key criteria, explanatory
519 and predictive power, benchmarking it against established frameworks such as the TPB and
520 the NAM, both of which are integrated into the analysis. The former phase indicated that
521 CBDM-BBP (Model 3) explains a greater proportion of variance in use behaviour compared
522 to TPB and NAT (Models 1 and 2), which are established frameworks (Hair et al., 2022; Ozili,
523 2023). The SRMR values indicate an acceptable fit across all models, though the NFI scores
524 fall below the recommended threshold, with Model 3 showing a marginally better fit. However,
525 Hair et al. (2022) argue that model fit statistics have limited value in PLS-SEM and may
526 compromise predictive power. They stress that PLS-SEM prioritises prediction over
527 explanation, requiring a different validation approach. Gregor (2006) and Sharma et al. (2022)
528 emphasise the importance of considering both explanatory and predictive approaches since
529 most management models integrate both.

530 Moving to the predictive approach (accuracy of predicting data not previously analysed),
531 results from out-of-sample prediction techniques confirmed the superior predictive relevance
532 of Model 3. Additionally, Model 3 consistently outperformed the naïve and conservative linear
533 model benchmarks, demonstrating higher predictive accuracy and robustness. Therefore, this
534 study underscores the efficacy of Model 3 (CBDM-BBP) in enhancing explanatory and
535 predictive capabilities compared to established models (TPB and NAT). By integrating

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multiple theoretical frameworks and considering a broader range of factors influencing consumer behaviour toward biobased products, the CBDM-BBP provides a better fit to the data. It also enhances predictive accuracy and reduces errors when forecasting previously unseen data. This approach offers a robust framework for understanding and predicting consumer decisions in the biobased product sector.

5.2 Key behavioural insights

While the CBDM-BBP presents a robust framework, our findings clearly demonstrate that behaviour in the biobased domain is shaped by both internal and external factors, as also highlighted by Nejadrezaei et al. (2024). Specifically, the results show that participants simultaneously expressed self-interested motivations alongside other-oriented concerns, such as environmental impact and societal responsibility.

In contrast to the assumptions of the TRA (Fishbein & Ajzen, 1975) and the TPB (Ajzen, 1991), decision-making in this context is neither solely self-interested nor purely altruistic, as suggested by Schwartz's NAT (1977). Instead, it reflects a combination of motivations encompassing self-interest, concern for others, and environmental responsibility.

This integrative pattern is evident in our framework, where attitudes primarily reflect personal benefits, while norms capture pro-social and environmental concerns, consistent with the themes identified in our results. Similar combinations of motivations have been reported in pro-environmental behaviour (Bamberg & Möser, 2007; Fallah Zavareh et al., 2020; Janmaimool & Denpaiboon, 2016; Klöckner & Blöbaum, 2010), as well as in other fields such as sustainable agriculture and responsible consumption (Asadi et al., 2021; Jain et al., 2020; Parker et al., 1995; Savari et al., 2023).

The model further highlights that behaviour is not merely the outcome of contextual and attitudinal factors, as proposed by Stern (2000) and Salonen and Åhlberg (2012), but is also

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strongly shaped by social influences observed in our data, particularly perceived peer pressure. For instance, the results indicate that consumers' willingness to purchase biobased products increased when such products were endorsed or normalised within their social circles. This finding supports Ajzen's (1991) emphasis on subjective norms.

Trust also emerged as a crucial determinant in our results. Participants expressed varying levels of trust in products, manufacturers, government, and NGOs, while also highlighting the responsibility of these actors in ensuring quality and reducing perceived risk and uncertainty. The role of trust has likewise been emphasised in pro-environmental behaviour research (Pham et al., 2023) and observed across various empirical studies (Butkowski et al., 2020; Dhir et al., 2021; Friedrich, 2022; Klein et al., 2020; Nguyen et al., 2021; Niedermeier et al., 2021; Stahl et al., 2021; Zwicker et al., 2022).

While consumers' prior experience with novel products is often found to mitigate uncertainty and foster trust (Ajzen, 1991, 2020), our results do not indicate a moderating role of past behaviour in the decision-making process. The absence of significant moderating effects of past behaviour suggests that, in the biobased product context, these relationships may be less sensitive to contextual variation than previously assumed, pointing to the need for further research into how experience shapes trust and decision-making in emerging product domains.

Furthermore, our findings suggest that consumers perceived behavioural control, particularly their ability to access and afford biobased products, significantly influences their decision-making. This aligns with prior studies identifying perceived behavioural control as a key determinant of behaviour (Ajzen, 1991, 2020; Chaudhary & Bisai, 2018; La Barbera & Ajzen, 2020, 2021).

5.3 Theoretical contribution of the CBDM-BBP

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583 The CBDM-BBP provides a structured pathway illustrating how consumers progress from
584 initial interest in biobased products to their eventual use. Unlike prior models such as Rogers'
585 DoI (2003) and Lavidge & Steiner's HoE Model (1961), the CBDM-BBP captures how
586 behavioural determinants evolve across stages. This dynamic progression is evident in our
587 findings: the results suggest a sequence from positive attitudes and initial interest to intention,
588 willingness to pay, and ultimately use behaviour.

589 Although this multi-stage progression has been partially reflected in previous studies (Liu et
590 al., 2020; Sajincic et al., 2021; Stahl et al., 2021), the CBDM-BBP makes a more explicit
591 contribution by integrating behavioural theory with contextual influences. Contextual factors
592 are shown to exert a direct influence throughout this behavioural process (Al-Hassan et al.,
593 2010; Halder et al., 2016; Klein et al., 2019; Nguyen et al., 2016; Notaro, Paletto, et al., 2022;
594 Nyangau et al., 2022; Scherer et al., 2018).

595 Unlike Stern's ABC Theory (2000), which focuses on the interaction between attitudes and
596 contextual conditions, the CBDM-BBP reveals that contextual variables (such as product
597 attributes, policy instruments, PBC) moderate the relationships between values, trust, and
598 behavioural determinants. This area has been relatively underexplored in previous research.
599 Collectively, these insights support the development of a more refined, predictive, and context-
600 sensitive theoretical framework. By adopting such a comprehensive model, stakeholders can
601 gain a more holistic and nuanced understanding of the complex drivers of consumer behaviour
602 in the biobased sector.

603 **5.4 Limitations**

604 While the proposed model improves explanatory power, it also introduces increased
605 complexity compared to TPB and NAT. This complexity is reflected not only in the number of
606 constructs and relationships, but also in the analytical process required for model estimation

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and interpretation. In contrast, simpler models may capture key behavioural relationships more parsimoniously and with lower analytical demands. Therefore, the trade-off between model complexity, analytical effort, and parsimony should be carefully considered when applying the framework.

A further limitation relates to the model's emphasis on psychological determinants of behaviour as the primary basis of the framework. While product attributes and policy instruments are incorporated as moderating factors, their role may be underrepresented, particularly in contexts such as packaging where material characteristics are highly relevant. In addition, respondents evaluated the general concept of biobased products across multiple packaging applications rather than specific products with clearly defined characteristics. While this supports the development of a broadly applicable behavioural framework across different product contexts, the identified relationships may not fully capture product-specific behavioural mechanisms. Consequently, the model may not fully capture all factors that directly influence user behaviour in real-world settings. Future research should therefore validate the framework within specific product categories and use contexts.

A further limitation relates to the domain-specific validation of the proposed framework. The CBDM-BBP was developed and empirically tested within the context of biobased products, which may limit the generalisability of the findings. Although the model is not inherently exclusive to this domain, its applicability to other product categories (e.g., organic products or other sustainable innovations) has not been established within this study. Consequently, the transferability and robustness of the model across different contexts remain uncertain and require further empirical investigation. Future research should therefore examine the model in alternative domains to assess its broader applicability and external validity.

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Regarding the generalisability of the findings, given the inherent socio-cultural and institutional diversity across countries, the results should be interpreted with appropriate caution. The generalisability of the findings beyond the Irish context may therefore be limited. Nevertheless, the proposed framework is grounded in established behavioural theories and was developed to capture fundamental psychological and contextual determinants of consumer behaviour. As such, while the strength and significance of specific relationships may vary across contexts, the framework provides a useful basis for examining biobased product adoption in different geographical settings. Future research should assess its applicability across countries and cultural contexts.

6. Conclusion

This study advances the theoretical understanding of consumer behaviour towards biobased products by developing and validating the Comprehensive Behavioural Decision Model for Biobased Products (CBDM-BBP). By integrating cognitive and normative perspectives, the model offers a more holistic lens through which to examine the complex dynamics underlying consumer decisions in this emerging domain.

The findings contribute to the literature by elucidating the pathways through which values and trust shape key behavioural determinants, such as interest, intention, willingness to pay, and use behaviour. Moreover, the study provides valuable insight into how these determinants evolve across behavioural stages and are influenced by contextual moderators, thereby supporting the development of a more nuanced, predictive, and context-sensitive theoretical framework.

The proposed framework offers practical guidance for stakeholders, including policymakers and practitioners, by identifying key behavioural mechanisms that influence the adoption of

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biobased products. Rather than prescribing specific policy measures, the model enables the identification of leverage points for intervention.

For instance, the prominence of early-stage behavioural determinants and trust suggests that strategies aimed at increasing awareness and reducing uncertainty, such as transparent communication and certification schemes, may be particularly effective. Similarly, the influence of social and personal norms indicates that interventions targeting social influence, including public campaigns or endorsements from trusted individuals and institutions, could support behavioural change.

In addition, the framework highlights the relevance of contextual and structural factors, suggesting that economic or regulatory instruments (e.g., incentives or labelling schemes) may complement psychological drivers of behaviour. These examples illustrate how the model can be applied to inform the design of targeted interventions, while maintaining flexibility across different contexts and applications.

Future research could further strengthen the validation and refinement of the CBDM-BBP by exploring the balance between model complexity and parsimony, as well as by incorporating additional contextual and product-specific variables. Expanding the model to include factors such as functional attributes and policy influences may provide a more comprehensive understanding of consumer behaviour.

Furthermore, applying the proposed framework across diverse geographical settings and different biobased product applications would enable a more robust assessment of its generalisability and transferability. Cross-context validation would help evaluate the model's applicability across varying cultural, economic, and environmental conditions.

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Overall, such efforts would contribute to enhancing the robustness and broader applicability of the CBDM-BBP, while advancing methodological approaches to understanding consumer behaviour in the context of sustainable products.

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Appendices

Appendix A. Survey Items

Awareness of Consequences (AC, 3 Items, Cronbach's alpha = 0.86)

- AC1: I am concerned about the impact of fossil-based products on greenhouse gas emissions (GHG).
- AC2: I am concerned about waste generation as a result of fossil-based products.
- AC3: Overall, fossil-based products can have some negative consequences.

Ascription of Responsibility (AR, 3 Items, Cronbach's alpha = 0.90)

- AR1: I feel responsible for the contribution of fossil-based products to greenhouse gas (GHG) emissions.
- AR2: I feel responsible for the contribution of fossil-based products to waste generation.

- AR3: I feel responsible for the negative consequences of fossil-based products.

Awareness (Awa, 3 Items, Cronbach's alpha = 0.85)

- Awa1: Before this survey, to what extent had you already heard about biobased plastics in the media, on social media, in news coverage, etc?
- Awa2: How familiar, or not, are you with Biobased plastic products in the market?
- Awa3: How familiar, or not, are you with Biobased plastic brands in the market?

Subjective Knowledge (Know-Sub, 1 item)

- Know-Sub1: I have a good knowledge of biobased plastic products.

Objective Knowledge (Know-Obj, 9 item, Cronbach's alpha = 0.79)

Based on your own knowledge, are the following statements true or false?

- Know-Obj1: The term 'biobased plastics' refers to plastics that are partly or entirely made from renewable biological materials such as plants and/or waste, but often still contain fossil fuels.
- Know-Obj2: Biobased plastics are not necessarily biodegradable or compostable.
- Know-Obj3: Biobased plastics whether they are biodegradable/compostable or not, can be recycled.
- Know-Obj4: Putting biodegradable plastics into the environment will make them break down quickly.
- Know-Obj5: I can compost biodegradable plastics at home.
- Know-Obj6: Biodegradable plastics are plastics that can, under certain environmental conditions, be broken down into natural materials.
- Know-Obj7: Putting compostable plastics into the environment will make them break down.
- Know-Obj8: I can compost all compostable plastics at home.

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- Know-Obj9: Plastics that are compostable can decompose or biodegrade fully under the specific conditions of an industrial composting facility.

Perception (Perc, 6 Items, Cronbach's alpha = 0.67)

- Perc1: The use of biobased plastics contributes to a decrease in the amount of waste generated.
- Perc2: The use of biobased plastics contributes to a reduction in greenhouse gas emissions.
- Perc3: The use of biobased plastics contributes to creating sustainable economic growth and new jobs.
- Perc4: The use of biobased plastics reduces dependence on non-renewable resources like fossil fuels.
- Perc5: Increasing the production and consumption of biobased plastics competes with food crops and decreases food production.
- Perc6: Increasing the consumption of biobased plastics increases food prices.

Past Behaviour (PB, 1 Item)

- PB 1: Have you purchased or do you own any biobased products?

Attitude (Att, 5 Items, Cronbach's alpha = 0.91)

- Att1: For me, using biobased plastic packaging for packaging in the future will be pleasant.
- Att2: For me, using biobased plastic packaging for packaging in the future will be beneficial.
- Att3: For me, using biobased plastic packaging for packaging in the future will be valuable.
- Att4: For me, using biobased plastic packaging for packaging in the future will be enjoyable.

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- Att5: Overall, in the future do you think biobased packaging will be good.

Social Norms (SN, 4 Items, Cronbach's alpha = 0.81)

- SN1: The people in my life whose opinion I value would approve of my future use of products packaged with biobased plastic.
- SN2: Most people who are important to me think that I should use products with biobased plastic packaging in the future.
- SN3: Most people who are important to me use products with biobased plastic packaging.
- SN4: The people in my life whose opinions I value use products with biobased plastic packaging.

Personal Norms (PN, 3 Items, Cronbach's alpha = 0.87)

- PN1: I feel morally obligated to use products with biobased plastic packaging.
- PN2: Products with biobased plastic packaging are consistent with my moral principles, values, and beliefs.
- PN3: I feel guilty if I do not use products with biobased plastic packaging.

Trust (Tru, 5 Items, Cronbach's alpha = 0.71)

- Tru1: I trust biobased plastic packaging for packaging products in the future.
- Tru2: I do not trust manufacturers regarding the claimed quality and features of the biobased plastic packaging.
- Tru3: I trust government agencies to ensure the safety of products with biobased plastic packaging.
- Tru4: I trust non-profit organisations to ensure the sustainability and social justice of products with biobased plastic packaging.
- Tru5: I trust scientists and academia when it comes to evaluating the sustainability of biobased plastic packaging.

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Interest (Intr, 3 Items, Cronbach's alpha = 0.82)

- Intr1: Thinking of the future, how likely or unlikely are you to use products with biobased plastic packaging?
- Intr2: I would prefer to use products with biobased plastic packaging than fossil-based products in future.
- Intr3: I would consider using products with biobased plastics in the future.

Willingness to Pay (WTP, 2 Items, Cronbach's alpha = 0.89)

- WTP1: Thinking of the future, how likely or unlikely are you to pay more for products with biobased plastic packaging.
- WTP2: I would definitely pay more for products with biobased plastic packaging in future.

Intention (Intt, 3 Items, Cronbach's alpha = 0.90)

- Intt1: I intend to use products with biobased plastic packaging in the future.
- Intt2: I plan to use products with biobased plastic packaging in the future.
- Intt3: I will use products with biobased plastic packaging in the future.

Product Attributes (PA, 20 Items, Cronbach's alpha = 0.88)

Thinking of products with biobased plastic packaging, how important or not, are each of the following attributes to you?

- PA1: The brand of packaged products in biobased plastic.
- PA2: Overall Price.
- PA3: Appearance (e.g., colour, shininess, transparency) of biobased plastic packaging.
- PA4: Leak-proof.
- PA5: Hygienic.
- PA6: Product protection (i.e. prevents damage to the product).
- PA7: Recyclability of biobased plastic packaging.

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- PA8: Reusability of biobased plastic packaging.
- PA9: Composability of biobased plastic packaging.
- PA10: Biodegradability of biobased plastic packaging.
- PA11: Crops (e.g., potato, corn, cereals, sugarcane) as a source material.
- PA12: Food waste (e.g., food leftover, coffee ground, orange peels, milk) as a source material.
- PA13: Plant waste (e.g., banana and pineapple peel, coconut husk) as a source material.
- PA14: Marine and fisheries waste (e.g., fish processing waste, fish skins) as a source material.
- PA15: Slaughterhouse waste (e.g., blood, tissues, horns, hooves) as a source material.
- PA16: Forestry waste (e.g., wood waste, forest waste, sawdust) as a source material.
- PA17: Landscape and pruning waste (e.g., grass, leaves, branches, weeds) as a source material.
- PA18: Genetically modified crops.
- PA19: Which, if any of the following, would be your preferred place of origin for source materials for products with biobased packaging?
- PA20. When considering products with biobased plastics, which of the following, if any, would be your biobased plastic composition?

Policy Interventions (PI, 11 Items, Cronbach's alpha = 0.93)

Thinking of other factors for products with biobased plastic packaging, how important or not, are the following factors to you?

- PI1: Having general sustainability-related information about biobased packaging on it.
- PI2: Having availability of health and safety-related information about biobased packaging on it.

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- PI3: Having availability of information on source materials (e.g., crop, waste) about biobased packaging on it.
- PI4: Having availability of end-of-life-related information (e.g., recycle, compost) about biobased packaging on it.
- PI5: Having a standard for biobased plastic packaging.
- PI6: Having labels/certification for biobased plastic packaging.
- PI7: Having regulation for biobased plastic packaging.
- PI8: Governmental incentives (e.g., tax-subsidies).

Thinking of products with biobased plastic packaging, how important or not, are each of the following factors to you?

- PI9: To be available in the market in the future.
- PI10: To be considered in making procurement decisions by Government agencies.
- PI11: To be visible in my daily life.

Perceived Behavioural Control (PBC, 3 Items, Cronbach's alpha = 0.67)

- PBC1: If I want to, I can use products in biobased plastic packaging.
- PBC2: For me to find products with biobased plastic packaging would be easy.
- PBC3: For me, products with biobased plastic packaging would be affordable.

Use behaviour (UB, 5 Items, Cronbach's alpha = 0.77)

- To what extent, if any, do you currently use or have you used in the past, the following types of products?
- UB1: Biobased coffee capsules.
- UB2: Biobased bags, containers or nets for fruit and vegetables.
- UB3: Biobased trays for meat.
- UB4: Biobased bottles for detergents.
- UB5: Biobased bottles for shampoos, body wash/shower gel, and soaps.

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Appendix B. Supplementary Tables

Table B.1. Characteristics of the respondents (n=525)

	Features	Frequency	Percent	CSO 2022
Gender	Male	257	49.0	49%
	Female	268	51.0	51%
Age	18-24	68	13.0	14%
Min = 18	25-34	91	17.3	18%
Max = 83	35-44	99	18.9	20%
Mean = 45.98	45-54	88	16.8	18%
Median = 45.00	55-64	74	14.1	14%
Std. Deviation = 16.56	+65	105	20.0	16%
Region	Dublin	138	26.3	29%
	RoL	139	26.5	26%
	Munster	146	27.8	27%
	Conn/Uls	102	19.4	18%
Social Class	ABC1F	240	45.7	47%
	C2DE	285	54.3	53%

Table B.2. Reflective measurement model assessment showing indicator reliability, convergent validity, and internal consistency reliability across all constructs.

Latent Variable	Indicators	Indicator Reliability - Outer Loadings	Convergent Validity - AVE	Internal Consistency Reliability - rho_A
AC	AC1-3	.86 - .94	.83	.91
AR	AR1-3	.95 - .95	.91	.95
Att	Att1-5	.75 - .88	.69	.89
Awa	Awa1-3	.85 - .92	.80	.87
Intr	Intr1-3	.85 - .90	.77	.85
Intt	Intt1-3	.93 - .94	.88	.93
Know_O	Know_O1-3	.74 - .85	.63	.74
Know _S	Know_S1	1.00	-	-
Perc	Perc1-4	.79 - .83	.65	.82
PN	PN1-3	.84 - .89	.74	.82
SN	SN1-4	.74 - .84	.64	.82
Trust	Tru1-5 (Excl. 2)	.74 - .83	.62	.80
UB	UB1-5	.72 - .82	.59	.82
WTP	WTP1-2	.92 - .93	.86	.84
PB	PB1	1.00	-	-
PBC	PBC2-3	.76 - .86	.66	.51

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Table B.3. Assessment of the reflective measurement model using the Heterotrait-Monotrait Ratio (HTMT) matrix to evaluate discriminant validity among the study constructs.

	AC	AR	Att	Awa	Intr	Intt	Know_O	Know_S	PB	PBC	PN	Perc	SN	Tru	UB	WTP
AC																
AR	.72															
Att	.48	.40														
Awa	.28	.28	.17													
Intr	.66	.54	.80	.29												
Intt	.62	.55	.72	.29	.89											
Know_O	.21	.13	.22	.50	.25	.22										
Know_S	.15	.21	.08	.87	.18	.22	.40									
PB	.21	.17	.24	.34	.24	.24	.12	.25								
PBC	.04	.11	.09	.29	.05	.06	.06	.31	.12							
PN	.63	.63	.70	.36	.77	.76	.24	.25	.26	.18						
Perc	.52	.42	.63	.27	.68	.65	.33	.19	.20	.07	.60					
SN	.41	.49	.53	.51	.59	.60	.29	.43	.29	.30	.84	.48				
Tru	.51	.48	.66	.27	.70	.71	.21	.17	.13	.15	.80	.67	.69			
UB	.16	.24	.17	.42	.25	.30	.10	.40	.21	.45	.36	.22	.46	.27		
WTP	.53	.57	.45	.42	.62	.62	.20	.38	.22	.31	.70	.43	.65	.56	.40	

Table B.4. Assessment of the formative measurement model showing indicator relevance, significance, and collinearity statistics for all formative constructs.

Paths	Decision making for formative indicators					VIF	Convergent Validity
	Outer Weights	p-value	Outer Loading	p-value	Result		
PA1 -> PA	.154	.002	.367	.000	Remains	1.181	.94
PA4 -> PA	-.202	.000	.227	.000	Remains	1.879	
PA5 -> PA	-.050	.326	.334	.000	Remains	1.908	
PA6 -> PA	.049	.353	.362	.000	Remains	1.821	
PA7 -> PA	.156	.017	.662	.000	Remains	2.691	
PA8 -> PA	.161	.018	.640	.000	Remains	2.253	
PA9 -> PA	.128	.082	.702	.000	Remains	3.102	
PA10 -> PA	.083	.252	.691	.000	Remains	2.940	
PA11 -> PA	.285	.000	.782	.000	Remains	2.113	
PA12 -> PA	.079	.441	.747	.000	Remains	3.706	
PA13 -> PA	.216	.006	.754	.000	Remains	3.534	
PA14 -> PA	-.046	.474	.425	.000	Remains	2.335	
PA15 -> PA	-.047	.422	.272	.000	Remains	1.884	
PA16 -> PA	.112	.171	.663	.000	Remains	2.902	
PA17 -> PA	.021	.801	.674	.000	Remains	3.365	
PA18 -> PA	.159	.001	.352	.000	Remains	1.256	
PA19 -> PA	.007	.883	.253	.000	Remains	1.141	
PA20 -> PA	.142	.005	.537	.000	Remains	1.314	
PI1 -> PI	.218	.008	.655	.000	Remains	2.393	.96
PI2 -> PI	.000	.998	.480	.000	Remains	2.539	

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Paths	Decision making for formative indicators					VIF	Convergent Validity
	Outer Weights	p-value	Outer Loading	p-value	Result		
PI3 -> PI	.046	.530	.506	.000	Remains	2.169	
PI4 -> PI	.087	.264	.554	.000	Remains	2.310	
PI5 -> PI	.029	.709	.465	.000	Remains	2.387	
PI6 -> PI	-.192	.024	.419	.000	Remains	2.693	
PI7 -> PI	-.035	.652	.451	.000	Remains	2.646	
PI8 -> PI	-.003	.960	.433	.000	Remains	1.438	
PI9 -> PI	.596	.000	.935	.000	Remains	2.303	
PI10 -> PI	.264	.000	.774	.000	Remains	1.792	
PI11 -> PI	.145	.040	.749	.000	Remains	1.996	

Table B.5. Assessment of collinearity within the structural (inner) model based on variance inflation factor (VIF) values.

Paths	VIF	Paths	VIF	Paths	VIF	Paths	VIF
AC -> PN	1.864	Intr -> UB	3.455	PN -> Intt	2.874	SN -> UB	2.128
AR -> PN	2.005	Intr -> WTP	3.413	PN -> UB	3.045	SN -> WTP	2.037
Att -> Intr	1.723	Intt -> UB	3.404	PN -> WTP	2.939	Tru -> Att	2.106
Att -> Intt	2.181	Intt -> WTP	3.322	Perc -> Att	1.568	Tru -> Intr	2.006
Att -> UB	2.241	Know_O -> Att	1.234	SN -> Att	2.302	Tru -> Intt	2.058
Att -> WTP	2.217	Know_S -> Att	3.057	SN -> Intr	2.030	Tru -> UB	2.110
Awa -> Att	3.312	PN -> Att	2.498	SN -> Intt	2.031	Tru -> WTP	2.110
Intr -> Intt	2.427	PN -> Intr	2.676	SN -> PN	1.257	WTP -> UB	1.759

Table B.6. Structural model assessment for the TPB, NAT, and CBDM-BBP models, including path coefficients, statistical significance (p-values), and effect sizes of the hypothesised relationships.

Models	Paths	Original Sample (O)	p-value	f^2 Effect Size
TPB	Att -> Intt	.524	.000***	.431
	SN -> Intt	.290	.000***	.132
	Intt -> UB	.259	.000***	.078
	PBC x Intt -> UB	.051	.282	.003
NAT	AC -> PN	.320	.000***	.089
	AR -> PN	.349	.000***	.105
	PN -> UB	.305	.000***	.103
CBDM-BBP	Awa -> Att	-.020	.720	.000
	Know_O -> Att	.052	.144	.004
	Know_S -> Att	-.103	.083	.007
	Perc -> Att	.260	.000***	.082
	AC -> PN	.259	.000***	.090
	AR -> PN	.152	.001***	.029
	Att -> Intr	.435	.000***	.266
	Att -> Intt	.103	.014*	.016
	Att -> WTP	-.118	.039*	.011
	Att -> UB	-.121	.050*	.008
	Tru -> Intr	.146	.001***	.026
	Tru -> Intt	.125	.002**	.025

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Models	Paths	Original Sample (O)	p-value	f^2 Effect Size
	Tru -> WTP	.013	.812	.000
	Tru -> UB	-.026	.647	.000
	SN -> Intr	.018	.657	.000
	SN -> Intt	.041	.293	.003
	SN -> WTP	.228	.000***	.045
	SN -> UB	.288	.000***	.048
	PN -> Intr	.286	.000***	.074
	PN -> Intt	.139	.004**	.022
	PN -> WTP	.246	.000***	.036
	PN -> UB	.029	.699	.000
	Tru -> Att	.188	.001**	.032
	SN -> Att	.053	.268	.002
	PN -> Att	.336	.000***	.086
	SN -> PN	.533	.000***	.566
	Intr -> Intt	.545	.000***	.406
	Intr -> WTP	.156	.025*	.012
	Intr -> UB	-.055	.476	.001
	Intt -> WTP	.216	.001**	.025
	Intt -> UB	.126	.096	.006
	WTP -> UB	.190	.001	.025
	PBC x Att -> Intr	-.079	.032*	.013
	PBC x Att -> Intt	.029	.369	.002
	PBC x Att -> UB	-.056	.361	.003
	PBC x Att -> WTP	-.001	.980ns	.000
	PA x PN -> Intr	-.041	.565ns	.001
	PA x PN -> Intt	-.130	.042*	.011
	PA x PN -> UB	.077	.435ns	.001
	PA x PN -> WTP	-.097	.316ns	.003
	PI x PN -> Intr	.018	.816ns	.000
	PI x PN -> Intt	.156	.020*	.015
	PI x PN -> UB	-.097	.297ns	.002
	PI x PN -> WTP	.084	.364ns	.002
	PBC x PN -> Intr	.081	.100ns	.006
	PBC x PN -> Intt	-.149	.001**	.028
	PBC x PN -> UB	.210	.009**	.020
	PBC x PN -> WTP	.029	.664ns	.001
	PI x SN -> Intr	.077	.189ns	.004
	PI x SN -> Intt	-.073	.316ns	.005
	PI x SN -> UB	.040	.645ns	.000
	PI x SN -> WTP	-.109	.167ns	.005
	PB x SN -> Intr	-.132	.346ns	.003
	PB x SN -> Intt	.063	.523ns	.001
	PB x SN -> UB	.299	.139ns	.006
	PB x SN -> WTP	-.126	.463ns	.002
	PA x SN -> Intr	.023	.693ns	.000
	PA x SN -> Intt	.053	.414ns	.002
	PA x SN -> UB	.044	.626ns	.001
	PA x SN -> WTP	.059	.490ns	.001
	PBC x SN -> Intr	.004	.919ns	.000
	PBC x SN -> Intt	.042	.258ns	.003
	PBC x SN -> UB	-.146	.017*	.014

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Models	Paths	Original Sample (O)	p-value	f^2 Effect Size
	PBC x SN -> WTP	-.002	.977^{ns}	.000
	PI x Tru -> Intr	-.032	.510^{ns}	.001
	PI x Tru -> Intt	-.084	.070^{ns}	.009
	PI x Tru -> UB	.039	.605^{ns}	.001
	PI x Tru -> WTP	.088	.198^{ns}	.005
	PI x Att -> Intr	.009	.891^{ns}	.000
	PI x Att -> Intt	-.086	.158^{ns}	.008
	PI x Att -> UB	.031	.671^{ns}	.000
	PI x Att -> WTP	-.071	.413^{ns}	.003
	PB x Tru -> Intr	.002	.991^{ns}	.000
	PB x Tru -> Intt	-.137	.247^{ns}	.003
	PB x Tru -> UB	-.080	.682^{ns}	.000
	PB x Tru -> WTP	-.003	.984^{ns}	.000
	PB x Att -> Intr	.172	.181^{ns}	.006
	PB x Att -> Intt	-.087	.392^{ns}	.002
	PB x Att -> UB	.076	.640^{ns}	.001
	PB x Att -> WTP	-.071	.659^{ns}	.001
	PBC x Tru -> Intr	.001	.977^{ns}	.000
	PBC x Tru -> Intt	.053	.155^{ns}	.006
	PBC x Tru -> UB	.012	.836^{ns}	.000
	PBC x Tru -> WTP	-.019	.766^{ns}	.000
	PB x PN -> Intr	-.148	.465^{ns}	.002
	PB x PN -> Intt	.078	.566^{ns}	.001
	PB x PN -> UB	-.195	.446^{ns}	.002
	PB x PN -> WTP	.035	.876^{ns}	.000
	PA x Att -> Intr	-.029	.641^{ns}	.001
	PA x Att -> Intt	.009	.870^{ns}	.000
	PA x Att -> UB	-.039	.625^{ns}	.001
	PA x Att -> WTP	.118	.146^{ns}	.009
	PA x Tru -> Intr	-.016	.796^{ns}	.000
	PA x Tru -> Intt	.173	.002**	.030
	PA x Tru -> UB	-.089	.274^{ns}	.003
	PA x Tru -> WTP	-.038	.630^{ns}	.001

ns: Not Significant

* 95% confidence level (.05 sig level); ** 99% confidence level (.01 sig level); *** 99.9% confidence level (.001 sig level)

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