Journal of Electronic Business & Digital Economics

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# Personality-driven participation in digital platforms: evidence from reinforcement sensitivity theory

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Received 28 September 2025
Revised 22 October 2025
Accepted 15 December 2025

## Abstract

**Purpose** – We investigate why some people lean into platform-mediated collaborative consumption while others hold back. Using reinforcement sensitivity theory (RST), we examine how the behavioural activation system (BAS) and behavioural inhibition system (BIS) relate to perceived enjoyment, economic value, sustainability and social recognition – and how those perceptions shape attitudes and intentions to participate.
**Design/methodology/approach** – We surveyed 302 US consumers who are familiar with services such as Airbnb and Uber. Established scales captured BAS/BIS and perceived platform benefits. Analyses followed a two-step structural equation modelling procedure in AMOS: confirmatory factor analysis and then the structural model.
**Findings** – BAS consistently predicted stronger perceived benefits – especially enjoyment, economic value and sustainability – and, more modestly, social recognition. BIS added little explanatory power overall, aside from a weak association with social recognition. Enjoyment, economic value and sustainability were each linked to more favourable attitudes, which strongly predicted participation intentions.
**Practical implications** – To attract high-BAS users, enjoyable experiences, savings and sustainability are emphasised. High-BIS users respond better to risk reduction: clear policies, privacy safeguards and credible feedback systems. Tailoring communication and design to these profiles can support adoption and retention. In practice, platforms can design messages and features that build trust for cautious users and highlight enjoyment and value for those who seek positive experiences.
**Originality/value** – The study links personality psychology to digital-platform participation. Applying RST in an electronic-business setting shows how motivational differences help explain heterogeneity in user perceptions and behaviour.

**Keywords** Digital platforms, Electronic business, Digital economy, Sharing economy, Collaborative consumption, Participation, Personality, BIS/BAS, Reinforcement sensitivity theory, Trust, Platform design, Structural equation modelling

**Paper type** Research article

## 1. Introduction

The rapid expansion of digital platforms has reshaped everyday consumption. Services such as Airbnb and Uber allow people to exchange goods and services directly, bypassing traditional providers. This change, enabled by digital technologies (see, e.g. Trabelsi, 2024), has also altered the meaning of ownership. Instead of buying products outright, many consumers now prefer collaborative consumption (CC), which emphasises access and sharing over possession (Bardhi & Eckhardt, 2012; Belk, 2014; Eckhardt *et al.*, 2019; Lamberton & Rose, 2012).



*Funding:* This work was supported by Shenzhen Philosophy and Social Sciences Planning Project, Research on Shenzhen's implementation of the national cultural digitalization strategy and award id: SZ2023B017 and Research Foundation of Shenzhen Polytechnic University and award id: 6022312032S.

Journal of Electronic Business & Digital Economics
Vol. 5 No. 1, 2026
pp. 3-18
Emerald Publishing Limited
e-ISSN: 2754-4222
p-ISSN: 2754-4214
DOI 10.1108/JEBDE-09-2025-0088

Digital business platforms are also economic systems that connect consumers and companies to create and share value. As Rangaswamy *et al.* (2020) point out, marketing has an important role in managing these platforms and shaping how they create value. This view helps explain why individual motivations matter in understanding participation in platform-based consumption. Recent studies show that digital transformation changes how value is created for consumers, companies, and society. It also calls for using ideas from different fields to better understand how platform ecosystems work (Gawer, 2022; Paul *et al.*, 2024; Wegner, da Silveira, Marconatto, & Mitrega, 2024).

While CC promises economic, social, and environmental benefits, its success ultimately depends on what motivates consumers and the degree of trust they place in platform environments (Gu, Zhang, Lu, & Song, 2021; Kansal & Bhalla, 2023; Li & Wen, 2019; Möhlmann, 2015; Tanveer, Agung Sahara, Kremantzis, & Ishaq, 2025; Tussyadiah & Pesonen, 2018; Zhu, So, & Hudson, 2017). Yet the model also brings challenges. Critics note, for example, that Airbnb may contribute to higher housing costs for local residents (Bardhi and Eckhardt, 2012). Others highlight concerns over privacy and data security (Huynh & Gurtner, 2023). Similar concerns have been noted in wider debates on automation and digitalisation (Willcocks, 2024).

To address these mixed outcomes, we draw on reinforcement sensitivity theory (RST), a psychological framework for explaining differences in motivation and behaviour (Gray, 1982, 1990; Corr, 2004). Although originally developed in psychology, RST has been applied in marketing and consumer research to show why people respond differently to the same marketplace context (Carver & White, 1994; Corr & McNaughton, 2012; Corr & Cooper, 2016; Gligor, Esmark, & Holcomb, 2023; Arnold & Reynolds, 2012).

Our focus is on how RST explains variation in the way consumers perceive the benefits of CC delivered through digital platforms. We consider four benefit categories—enjoyment, economic value, sustainability, and social recognition—that capture functional, emotional, and social dimensions of value in settings such as ride-sharing (Chen & Zhou, 2025). Enjoyment refers to the positive experiences people gain from participation (Oliveira, Barbeitos, & Calado, 2022; Christodoulides, Athwal, Boukis, & Semaan, 2021). Economic value relates to cost savings or financial incentives, often achieved by making underused resources—such as housing—more accessible (Hamari, Sjöklint, & Ukkonen, 2016; Roma, Panniello, & Lo Nigro, 2019). Sustainability captures the environmental advantages of sharing, including reduced waste and healthier transport choices like bike-sharing (Piscicelli, Cooper, & Fisher, 2015; Zhu & Liu, 2021). Social recognition involves status or acknowledgement within platform communities (Kankanhalli, Tan, & Wei, 2005; Wasko & Faraj, 2005).

Trust is intertwined with these benefits. Platforms depend on mechanisms such as ratings and reviews to help participants manage uncertainty in exchanges with strangers (ter Huurne, Ronteltap, Corten, & Buskens, 2017; Tussyadiah & Pesonen, 2018). Relational benefits such as confidence, social connection, and personal trust further encourage loyalty and continued use (Yang, Song, Chen, & Xia, 2017). For instance, when booking accommodation from a private host via Airbnb, trust in both the host and the platform is essential (Mauri, Minazzi, Nieto-García, & Viglia, 2018).

This study focuses on one main research question, supported by two sub-questions:

*RQ1.* How do BIS and BAS traits shape consumers' perceptions of collaborative-consumption benefits and participation intentions on digital platforms?

*RQ1a.* How do BIS/BAS traits influence perceived enjoyment, economic value, sustainability, and social recognition?

*RQ1b.* How do those perceptions translate into attitudes and, in turn, into participation intentions?

By applying RST in the context of digital platforms, we extend theory and demonstrate how psychological perspectives can deepen understanding of consumer behaviour in digital marketplaces. The paper proceeds as follows: Section 2 reviews the literature, Section 3

presents the theoretical model and hypotheses, Section 4 explains the methodology, Section 5 reports the empirical results, and Section 6 discusses implications and future research directions.

## 2. Literature review

### *2.1 Collaborative consumption and consumer motivations*

CC has emerged as an important alternative to conventional consumption models. Its defining feature is the way it enables direct exchanges between consumers, often bypassing traditional providers. Digital platforms such as Airbnb and Uber have scaled up this form of interaction, reshaping established habits of consumption (Belk, 2014; Bardhi & Eckhardt, 2012; Say, Guo, & Chen, 2021).

The reasons why people participate in CC are diverse. Economic incentives remain central: many users are motivated by lower costs or opportunities to earn extra income (Möhlmann, 2015). Others value the novelty and variety of experiences or the opportunities for social interaction that platforms provide (Bardhi & Eckhardt, 2012). Sustainability has also been identified as a key driver, as consumers increasingly see sharing as an environmentally responsible choice (Hamari *et al.*, 2016; Piscicelli *et al.*, 2015). Beyond these, social recognition can play a role: active participation may enhance an individual's standing within platform communities (Kankanhalli *et al.*, 2005; Wasko & Faraj, 2005).

Trust, however, underpins all of these motivations. In the absence of the formal guarantees that come with traditional consumption, users rely heavily on peer reviews, ratings, and social feedback systems (Ert, Fleischer, & Magen, 2016; Hawlitschek, Teubner, & Gimpel, 2018). A lack of trust can quickly erode willingness to engage (Bardhi and Eckhardt, 2012; Gu *et al.*, 2021; Hofmann, Hartl, & Penz, 2017; Kansal & Bhalla, 2023; Lee, Jung, & Lee, 2021; Zhang, Yan, & Zhang, 2018; Zhu *et al.*, 2017). Well-designed governance mechanisms—such as transparent policies, clear rules, and credible reputation systems—are therefore essential to reduce uncertainty and promote participation (Osman, D'Acunto, & Johns, 2019; Jiang, Li, & Tang, 2024; Lu, Wang, & Zhang, 2021).

Social recognition interacts with trust in complex ways. Users often manage their online presence carefully to build credibility and reputation (Mikołajewska-Zając, 2018). Yet, the design of reputation systems raises ongoing concerns about fairness, bias, and the broader ethics of algorithmic decision-making (Zhu *et al.*, 2017; Smillie *et al.*, 2006; Sun, Kim, & Lee, 2022; Huang, Li, Huang, & Zhou, 2021; Chameroy, Salgado, de Barnier, & Chaney, 2024).

Although much of the literature has focused on economic, experiential, and environmental benefits, less attention has been paid to the psychological foundations of participation (Möhlmann, 2015; Hawlitschek, Teubner, & Weinhardt, 2016; Kansal & Bhalla, 2023). Recent contributions begin to address this gap. Lorenzo-Romero, Alcalá-García, and Gómez-Borja (2024), for example, identified distinct Airbnb user segments shaped by both motivations and personality traits. Roos and Hahn (2017) applied the Theory of Planned Behaviour to show how personal values and norms predict CC participation. Tanveer *et al.* (2025) further demonstrated the role of social norms, habits, and economic incentives in shaping consumer behaviour.

Identity-based motivations also matter. Those who see themselves as environmentally responsible are more inclined to offer CC services such as carpooling (Hartl, Kamleitner, & Holub, 2020), although identity appears less decisive when it comes to accepting rides. Other psychological factors, including loyalty and comfort, help sustain long-term engagement but remain underexplored (Tajeddini, Rasoolimanesh, Gamage, & Martin, 2021).

Overall, participation in CC is shaped by a wide mix of economic, experiential, social, and ethical considerations. While prior work provides a strong base, there is still limited understanding of the psychological dimensions that drive participation in digital platforms. The next section introduces RST as a framework for addressing this gap.

*2.2 Reinforcement sensitivity theory and consumer behaviour*

RST has long been used in psychology to explain why people react differently to the same situations. At its core, the theory focuses on how individuals vary in their responsiveness to rewards and potential threats (Gray, 1982, 1990; Corr, 2004). Rather than treating motivation as a single process, RST distinguishes three interacting systems: the behavioural activation system (BAS), the behavioural inhibition system (BIS), and the Fight–flight–freeze system (FFFS). The FFFS is most relevant when immediate danger is present, while BAS and BIS are more closely linked to everyday consumer choices because they govern approach versus avoidance tendencies (Gray & McNaughton, 2000; Smillie, Pickering, & Jackson, 2006).

The BAS reflects a readiness to pursue rewards and opportunities. People with stronger BAS tendencies are typically more impulsive, more responsive to positive feedback, and more inclined to explore new experiences or take calculated risks (Carver & White, 1994; Corr & Cooper, 2016). Prior studies have also connected high BAS with adaptability, creativity, and intrinsic motivation—all qualities that help explain why such individuals are open to experimenting with new digital platforms and the benefits they offer (Gligor *et al.*, 2023).

The BIS, in contrast, is oriented toward caution. Individuals scoring high on BIS are more likely to anticipate negative consequences, to feel anxious in uncertain situations, and to prefer environments with clear rules and safeguards (Gray & McNaughton, 2000; Corr & McNaughton, 2012). In platform-mediated exchanges, these traits translate into a greater need for transparency, reliable governance mechanisms, and visible protections before committing to participation (Kim, 2019; Corr & Cooper, 2016).

Although RST was originally developed to account for emotional and behavioural differences, its applications now extend beyond psychology. Research has used it to shed light on topics such as mood regulation, health behaviour, creativity, and consumer decision-making (Arnold & Reynolds, 2012; Gligor *et al.*, 2023; Perkins, Arnone, & Corr, 2021; Bijttebier, Beck, Claes, & Vandereycken, 2009; Demianczyk, Jenkins, Henson, & Conner, 2014). In retailing, for example, Arnold and Reynolds (2012) showed how BAS and BIS predict hedonic shopping preferences in distinct ways, highlighting their practical value for understanding marketplace behaviour.

Taken together, these insights suggest that RST offers a useful lens for analysing consumer heterogeneity. BAS and BIS traits can help explain why some individuals are quick to see new digital platforms as exciting opportunities, while others approach them more hesitantly and with greater concern for risk. Bringing this perspective into the study of CC allows us to capture an important psychological dimension often missing from accounts focused only on economic or social factors.

## 3. Theoretical framework and hypotheses

Building on the literature reviewed above, this study examines how BAS and BIS traits shape consumer perceptions of the benefits associated with CC on digital platforms. We also test how these perceptions influence attitudes toward participation and, ultimately, behavioural intentions. The overall research model is presented in Figure 1.

We chose RST instead of broader personality models such as the Big Five (McCrae & Costa, 1997) or behavioural frameworks like the Theory of Planned Behaviour (Ajzen, 1991) because RST focuses directly on approach and avoidance motivation (Gray, 1982; Corr, 2004). Decisions to join or avoid digital platforms depend on reward seeking and risk control, so BAS and BIS provide a close fit for explaining how consumers judge benefits and decide to participate (Carver & White, 1994). New research also confirms that the BIS and BAS systems can be reliably measured and linked to emotions of anxiety and approach motivation (Franchina, Klackl, & Jonas, 2024). Recent studies also link low BIS and high BAS to approach-oriented and risk-taking behaviour in online environments (Molenda *et al.*, 2022).

RST provides a useful lens for explaining why consumers evaluate CC differently. Individuals with stronger BAS traits are typically motivated by the pursuit of rewards and

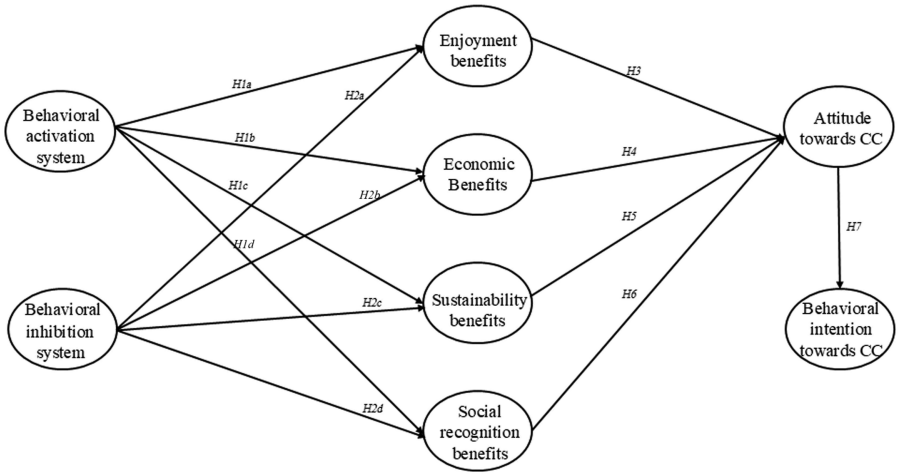


**Figure 1.** Conceptual model of BAS/BIS influences on collaborative consumption participation

positive experiences (Carver & White, 1994; Kim, 2019). Prior research indicates that such individuals are particularly sensitive to economic incentives and hedonic enjoyment (Arnold & Reynolds, 2012; Smillie *et al.*, 2006). Because BAS reflects a reward-seeking orientation, it is reasonable to expect that high-BAS consumers will perceive multiple benefits in platform participation.

*Hypotheses for BAS:*

*H1a.* BAS is positively associated with perceived enjoyment in CC.

*H1b.* BAS is positively associated with perceived economic benefits in CC.

*H1c.* BAS is positively associated with perceived sustainability benefits in CC.

*H1d.* BAS is positively associated with perceived social recognition benefits in CC.

By contrast, high-BIS individuals are more cautious, attentive to risk, and sensitive to potential threats. In digital-platform contexts, this tendency may limit their recognition of benefits. Empirical evidence here is limited, and strong effects are not necessarily expected, but it is still important to examine potential associations.

Because BIS is related to caution and sensitivity to risk, it is less likely to show strong positive links with perceived benefits compared to BAS. However, it is still important to test BIS effects, since clear rules and trustworthy platform features can shape how even cautious users see the value of participation.

*Hypotheses for BIS:*

*H2a.* BIS is positively associated with perceived enjoyment in CC.

*H2b.* BIS is positively associated with perceived economic benefits in CC.

*H2c.* BIS is positively associated with perceived sustainability benefits in CC.

*H2d.* BIS is positively associated with perceived social recognition benefits in CC.

Consumer attitudes are widely recognised as key predictors of behavioural intentions (Ajzen, 1991). Studies of CC confirm that when users perceive clear benefits—whether enjoyment, cost savings, sustainability, or social recognition—they tend to hold more favourable attitudes toward participation (Möhlmann, 2015; Zhu *et al.*, 2017).

*Hypotheses for perceived benefits and attitudes:*

*H3.* Perceived enjoyment is positively associated with consumer attitudes toward CC.

*H4.* Perceived economic benefits are positively associated with consumer attitudes toward CC.

*H5.* Perceived sustainability benefits are positively associated with consumer attitudes toward CC.

*H6.* Perceived social recognition benefits are positively associated with consumer attitudes toward CC.

Finally, attitudes are themselves powerful predictors of intentions to act (Ajzen, 1991; Fishbein & Ajzen, 1975). Consistent with previous CC research (Hamari *et al.*, 2016; Möhlmann, 2015), we expect:

*H7.* Positive attitudes toward CC are positively associated with behavioural intentions to participate in CC.

By combining RST with established theories of consumer behaviour, this framework highlights how personality-based motivations shape perceptions, attitudes, and participation intentions in digital platforms. The next section explains the methods used to test these hypotheses.

## 4. Method

This study employed a quantitative survey design. A structured questionnaire was developed from validated scales to measure BAS and BIS traits, perceived benefits of CC on digital platforms, attitudes, and behavioural intentions. In total, the instrument included 40 items. The full set of measures is reported in Table 1, and descriptive statistics and reliability indices are provided in Tables 1 and 2.

BAS and BIS were assessed with items adapted from Carver and White (1994). The BAS scale captures three subdimensions—Reward Responsiveness, Drive, and Fun Seeking—but following prior work, we modelled BAS as a single construct. Perceived enjoyment was measured with items adapted from van der Heijden (2004) (e.g. "I think CC is enjoyable," "I think CC is exciting"). Economic benefits were captured with measures from Bock, Zmud, Kim, and Lee (2005), such as "I can save money if I participate in CC." Sustainability was assessed with items from Hamari *et al.* (2016) (e.g. "Collaborative consumption helps save natural resources"). Social recognition was measured using items from Kankanhalli *et al.* (2005) and Wasko and Faraj (2005) (e.g. "Contributing improves my image within the community"). Attitudes were measured with items based on Ajzen (1991), such as "All things considered, participating in CC is wise." Finally, behavioural intentions were assessed using items from Bhalla and Kansal (2025), for example, "I expect to continue participating in CC often." All items were answered on five-point Likert scales (1 = strongly disagree, 5 = strongly agree).

Data collection was conducted through Amazon Mechanical Turk, a platform widely used in both consumer and psychological research (Chen and Zhou, 2025). The final dataset consisted of 302 responses from US consumers. This sample was chosen because US respondents are typically familiar with digital platforms such as Airbnb and Uber, making them a suitable context for testing our hypotheses.

The study involved anonymous survey responses, obtained with informed consent. Given the minimal risk to participants and the absence of identifying information, separate ethical approval was not required.

To test the research model, data were analysed using structural equation modelling (SEM). We adopted the two-step approach recommended in the SEM literature: first estimating the

**Table 1.** Results of the confirmatory factory analysis

| Construct and measures | Std. factor loadings |
|---|---|
| *Behavioural Activation System: Reward responsiveness (α = 0.806; AVE = 0.521; CR = 0.812)* | |
| 1. When I get something I want, I feel excited and energised | 0.80 |
| 2. When I'm doing well at something, I love to keep at it | 0.74 |
| 3. When good things happen to me, it affects me strongly | 0.74 |
| 4. It would excite me to win a contest | 0.60 |
| *Behavioural Activation System: Drive* (α = 0.816; AVE = 0.537; CR = 0.822) | |
| 5. When I want something, I usually go all-out to get it | 0.80 |
| 6. I go out of my way to get things I want | 0.74 |
| 7. If I see a chance to get something I want, I move on it right away | 0.75 |
| 8. When I go after something, I use a "no-holds-barred" approach | 0.63 |
| *Behavioural Activation System: Fun seeking* (α = 0.757; AVE = 0.533; CR = 0.77) | |
| 9. I crave excitement and new sensations | 0.87 |
| 10. I'm always willing to try something new if I think it will be fun | 0.70 |
| 11. I often act on the spur of the moment | 0.60 |
| *Behavioural inhibition system (α = 0.867; AVE = 0.568; CR = 0.868)* | |
| 12. If I think something unpleasant is going to happen I usually get pretty "worked up" | 0.70 |
| 13. I worried about making mistakes | 0.76 |
| 14. Criticism or scolding hurt me a bit | 0.77 |
| 15. I feel pretty worried or upset when I think or know somebody is angry at me | 0.79 |
| 16. I feel worried when I think I have done poorly something | 0.74 |
| *Enjoyment benefits from CC (α = 0.914; AVE = 0.736; CR = 0.917)* | |
| 17. I think collaborative consumption is enjoyable | 0.92 |
| 18. I think collaborative consumption is fun | 0.86 |
| 19. I think collaborative consumption is interesting | 0.75 |
| 20. I think collaborative consumption is pleasant | 0.89 |
| *Economic benefits from CC (α = 0.906; AVE = 0.777; CR = 0.912)* | |
| 21. I can save money if I participate in collaborative consumption | 0.91 |
| 22. My participation in collaborative consumption benefits me financially | 0.94 |
| 23. My participation in collaborative consumption can improve my economic situation | 0.79 |
| *Sustainability benefits from CC (α = 0.920; AVE = 0.687; CR = 0.917)* | |
| 24. Collaborative consumption helps save natural resources | 0.79 |
| 25. Collaborative consumption is a sustainable mode of consumption | 0.87 |
| 26. Collaborative consumption is ecological | 0.86 |
| 27. Collaborative consumption is efficient in terms of using energy | 0.80 |
| 28. Collaborative consumption is environmentally friendly | 0.82 |
| *Social recognition benefits from CC (α = 0.901; AVE = 0.704; CR = 0.904)* | |
| 29. Contributing to my collaborative consumption community improves my image within the community | 0.85 |
| 30. I gain recognition from contributing to my collaborative consumption community | 0.89 |
| 31. I would earn respect from others by sharing with other people in my collaborative consumption community | 0.89 |
| 32. People in the community who contribute have more prestige than those who do not | 0.71 |
| *Attitude towards CC (α = 0.950; AVE = 0.832; CR = 0.952)* | |
| 33. All things considered, I find participating in collaborative consumption to be a wise move | 0.90 |
| 34. All things considered, I think collaborative consumption is a positive thing | 0.94 |
| 35. All things considered, I think participating in collaborative consumption is a good thing | 0.93 |
| 36. Overall, sharing goods and services within a collaborative consumption community makes sense | 0.88 |

(*continued*)

**Table 1.** Continued

| Construct and measures | Std. factor loadings |
|---|---|
| *Behavioural intention towards CC (α = 0.936; AVE = 0.748; CR = 0.937)* | |
| 37. All things considered, I expect to continue collaborative consumption often in the future | 0.86 |
| 38. I can see myself engaging in collaborative consumption more frequently in the future | 0.91 |
| 39. I can see myself increasing my collaborative consumption activities if possible | 0.69 |
| 40. It is likely that I will frequently participate in collaborative consumption communities in the future | 0.89 |

**Note(s):** $N$ = 302; Goodness-of-fit indexes (GFI) = 0.809; ($\chi^2$ = 1435.686 and with degree of freedom (d.f.) = 694, Normed chi square = 2.069; comparative fit index (CFI) = 0.922; Non-normed fit index (NNFI) = 0.913; root mean square of approximation (RMSEA) = 0.06;. $\alpha$ (composite reliability): $(\sum\lambda)^2/((\sum\lambda)^2 + \sum(\theta))$, λ: indicator loading, θ: indicator error variance. All items measured with a seven-point scale with 1 = "strongly disagree" to 5 = "strongly agree" scale anchors

measurement model through confirmatory factor analysis (CFA), and then assessing the structural paths. Analyses were conducted in IBM AMOS. Established guidelines for SEM were followed throughout (Anderson & Gerbing, 1988; Bollen, 1989; Martínez-López, Gázquez-Abad, & Sousa, 2013; Sarstedt *et al.*, 2024; Williams, Vandenberg, & Edwards, 2009).

## 5. Results

### *5.1 Measurement model*

The measurement model was first assessed through CFA as part of the two-stage SEM procedure recommended by Anderson and Gerbing (1988). Analyses were conducted in IBM AMOS. Key CFA results are summarised in Table 2.

All factor loadings were above 0.70, indicating strong indicator reliability. The average variance extracted (AVE) for each construct exceeded the 0.50 threshold, supporting convergent validity. Composite reliability values were all greater than 0.70, demonstrating internal consistency. Discriminant validity was checked by comparing the square root of each construct's AVE with its correlations. Each construct shared more variance with its own indicators than with any other construct, as expected. In addition, MaxR(H) values were higher than the corresponding CRs, and AVE values exceeded maximum shared variance, providing further evidence of discriminant validity (Fornell & Larcker, 1981).

Overall, the model fit indices indicated a good fit to the data: $\chi^2$ = 1,435.686 (df = 694), comparative fit index (CFI) = 0.922, Tucker–Lewis index (TLI) = 0.913, root mean square of approximation (RMSEA) = 0.060. These values are consistent with commonly accepted thresholds (Bagozzi & Yi, 2012; Hu & Bentler, 1999), suggesting the measurement model was both reliable and valid.

### *5.2 Structural model and hypothesis testing*

The structural model also showed a satisfactory fit: $\chi^2$ = 1,523.478 (df = 710), RMSEA = 0.058, CFI = 0.918, TLI = 0.905. Figure 2 presents the main path results, and Table 3 reports the detailed hypothesis tests.

The results strongly supported hypotheses H1a–H1d. BAS was a significant predictor of enjoyment ($\beta$ = 0.784, $p$ < 0.001), economic benefits ($\beta$ = 0.806, $p$ < 0.001), sustainability ($\beta$ = 0.832, $p$ < 0.001), and, to a lesser extent, social recognition ($\beta$ = 0.383, $p$ < 0.001). This pattern highlights the central role of BAS in shaping perceptions of platform benefits.

**Table 2.** Means, standard deviations, composite reliabilities, AVEs, square roots of AVE and correlations

| | Mean | SD | CR | AVE | MSV | MaxR(H) | ATTI | ENJ | SUST | SOSI | BIS | BASRR | BASDR | BASFUN | ECON | INTE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ATTI | 5.564 | 1.166 | 0.952 | 0.832 | 0.748 | 0.955 | 0.912[a] | | | | | | | | | |
| ENJ | 5.328 | 1.130 | 0.917 | 0.736 | 0.734 | 0.931 | 0.857 | 0.858[a] | | | | | | | | |
| SUST | 5.372 | 1.064 | 0.917 | 0.687 | 0.540 | 0.919 | 0.735 | 0.625 | 0.829[a] | | | | | | | |
| SOSI | 3.954 | 1.327 | 0.904 | 0.704 | 0.182 | 0.918 | 0.271 | 0.330 | 0.427 | 0.839[a] | | | | | | |
| BIS | 2.676 | 0.699 | 0.868 | 0.568 | 0.040 | 0.870 | 0.105 | 0.023 | 0.129 | 0.144 | 0.754[a] | | | | | |
| BASRR | 3.289 | 0.488 | 0.812 | 0.521 | 0.440 | 0.825 | 0.356 | 0.331 | 0.333 | 0.025 | 0.199 | 0.722[a] | | | | |
| BASDR | 2.864 | 0.613 | 0.822 | 0.537 | 0.440 | 0.832 | 0.198 | 0.224 | 0.206 | 0.157 | −0.067 | 0.663 | 0.733[a] | | | |
| BASFUN | 2.632 | 0.655 | 0.770 | 0.533 | 0.207 | 0.819 | 0.114 | 0.166 | 0.095 | 0.297 | −0.014 | 0.364 | 0.455 | 0.730[a] | | |
| ECON | 5.575 | 1.185 | 0.912 | 0.777 | 0.584 | 0.934 | 0.764 | 0.653 | 0.681 | 0.205 | 0.044 | 0.315 | 0.178 | 0.062 | 0.882[a] | |
| INTE | 5.284 | 1.334 | 0.937 | 0.789 | 0.748 | 0.939 | 0.865 | 0.811 | 0.707 | 0.326 | 0.016 | 0.315 | 0.268 | 0.165 | 0.716 | 0.888[a] |

**Note(s):** ATTI, Attitude; ENJ, Enjoyment; SUST, Sustainability; SOSI, Social recognition; BIS, Behavioural inhibition system; BASRR, Behavioural Activation System, Reward Responsiveness; BASDR, Behavioural Activation System, Drive; BASFUN, Behavioural Activation System, Fun Seeking; ECON, Economic benefits; INTE, Behavioural intention. [a]Square Root of AVE. AVE (average variance extracted). ρv: $(\sum\lambda)2/(\sum\lambda 2 + \sum(\theta))$, λ: indicator loading, θ: indicator error variance. MSV (maximum shared variance). MaxR(H) (maximal reliability)

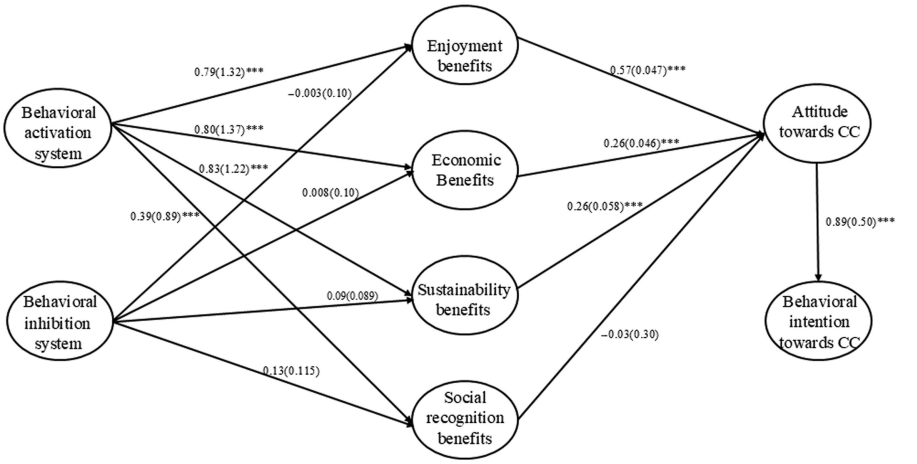


**Figure 2.** The final model: results of the final model with standardised (SE in parentheses) estimates

**Table 3.** Results of the hypothesis testing

| Hypothesis | Proposed relationship | Effect type | Path coefficient | Study result |
|---|---|---|---|---|
| H1a | BAS (+) Enjoyment benefits | Direct effect | $\beta = 0.784$, $p < 0.001$ | Supported |
| H1b | BAS (+) Economic Benefits | Direct effect | $\beta = 0.806$, $p < 0.001$ | Supported |
| H1c | BAS (+) Sustainability benefits | Direct effect | $\beta = 0.832$, $p < 0.001$ | Supported |
| H1d | BAS (+) Social recognition benefits | Direct effect | $\beta = 0.383$, $p < 0.001$ | Supported |
| H2a | BIS (+) Enjoyment benefits | Direct effect | $\beta = -0.03$, $p = 0.958$ | Not supported |
| H2b | BIS (+) Economic benefits | Direct effect | $\beta = 0.008$, $p = 0.899$ | Not supported |
| H2c | BIS (+) Sustainability benefits | Direct effect | $\beta = 0.098$, $p = 0.125$ | Not supported |
| H2d | BIS (+) Social recognition benefits | Direct effect | $\beta = 0.130$, $p = 0.044$ | Supported |
| H3 | Enjoyment benefits (+) Attitude | Direct effect | $\beta = 0.556$, $p < 0.001$ | Supported |
| H4 | Economic benefits (+) Attitude | Direct effect | $\beta = 0.257$, $p < 0.001$ | Supported |
| H5 | Sustainability benefits (+) Attitude | Direct effect | $\beta = 0.255$, $p < 0.001$ | Supported |
| H6 | Social recognition benefits (+) Attitude | Direct effect | $\beta = -0.30$, $p = 0.336$ | Not supported |
| H7 | Attitude (+) Behavioural intention | Direct effect | $\beta = 0.898$, $p < 0.001$ | Supported |

BIS, by contrast, did not significantly influence enjoyment ($\beta = -0.030$, $p = 0.958$), economic benefits ($\beta = 0.008$, $p = 0.899$), or sustainability ($\beta = 0.098$, $p = 0.125$). It did, however, show a weak but statistically significant positive association with social recognition

($\beta = 0.130$, $p = 0.044$). These findings suggest that BIS exerts only a limited influence on benefit perceptions.

Turning to the link between benefits and attitudes, enjoyment ($\beta = 0.556$, $p < 0.001$), economic benefits ($\beta = 0.257$, $p < 0.001$), and sustainability ($\beta = 0.255$, $p < 0.001$) all had significant positive effects, supporting H3, H4, and H5. Social recognition was not significant ($\beta = -0.030$, $p = 0.336$), so H6 was not supported.

Finally, attitudes strongly predicted behavioural intentions ($\beta = 0.898$, $p < 0.001$), providing full support for H7.

Together, these results show that BAS plays a decisive role in explaining how consumers perceive the benefits of digital platforms, while BIS has only a minor influence. Among the benefits, enjoyment, cost savings, and sustainability contribute most to positive attitudes, and those attitudes in turn are powerful predictors of intentions to participate.

## 6. Discussion and conclusion

### *6.1 Theoretical contribution*

This study applied RST to better understand why consumers engage with digital platforms for CC. By focusing on BAS and BIS traits, we add to prior work on motivations and trust in the sharing economy.

Our results confirm that consumers high in BAS consistently perceive stronger benefits from platform participation, including enjoyment, financial savings, sustainability, and—though to a lesser degree—social recognition. These findings align with earlier expectations that BAS reflects a reward-seeking orientation (Carver & White, 1994; Smillie *et al.*, 2006). In contrast, BIS showed only a limited role, with a weak link to social recognition but little explanatory power otherwise. This suggests that BIS-oriented users may be less responsive to platform benefits, unless strong assurances or risk-mitigating structures are in place.

The study contributes theoretically by demonstrating that psychological frameworks can enrich our understanding of consumer behaviour in digital markets. By integrating RST with platform research, we highlight how personality-based differences influence perceived value, attitudes, and intentions. This perspective broadens existing work on CC by adding a motivational dimension rooted in personality psychology.

### *6.2 Managerial implications*

The findings have practical implications for digital platforms. For users high in BAS, the most effective strategies emphasise rewards: enjoyable experiences, financial savings, and sustainability benefits. Communications and onboarding processes that highlight these aspects are likely to resonate.

High-BIS users, by contrast, respond less to rewards and more to assurances. To reach these consumers, platforms should stress trust-related features—such as security protocols, privacy protections, transparent policies, and credible feedback mechanisms. Messaging that directly addresses concerns about risk can lower barriers to participation. Platforms may also consider pairing trust-building measures with governance mechanisms that discourage opportunism, thereby strengthening credibility (Bhalla & Kansal, 2025).

Beyond segmentation, platforms can use personality-based strategies in three main areas. First, onboarding messages should highlight enjoyment and value for high-BAS users, and give clear information about rules and safety for high-BIS users. Second, design features such as verified identities, transparent ratings, and privacy options can help reduce uncertainty. Third, fair rules and visible ways to handle problems can increase trust. Together, these steps make participation easier for cautious users and more rewarding for those who seek positive experiences.

*6.3 Limitations and future research*

Like all studies, this one has its limitations. The sample was drawn from US consumers, which may restrict generalisability. Future work should test the model in other cultural contexts to examine whether the same personality-driven patterns hold.

A second limitation relates to BIS. Our findings suggest that BIS traits have little influence on perceptions of platform benefits, but this area remains underexplored. Further studies could focus more closely on BIS-oriented consumers, especially the role of trust and ethical safeguards.

Future research might also extend beyond RST. Integrating other personality frameworks, such as the Big Five, could help explain additional variation in platform participation. Finally, ethical issues—including fairness, transparency, and data privacy—deserve closer attention, particularly since they may be especially important for high-BIS consumers.

Future studies could also look more closely at how trust works in platform systems. For example, new work could examine how algorithms and reputation systems shape users' trust and willingness to participate (Chameroy *et al.*, 2024). Researchers could also use newer modelling tools, such as hybrid structural equation modeling–artificial neural networks approaches, to test complex patterns in platform behaviour (Leong, Hew, Ooi, & Chau, 2024). Finally, studies on power and fairness in platform governance (Bhalla & Kansal, 2025) could help explain how rules and safeguards influence cautious, high-BIS users.

*6.4 Conclusion*

This research shows how RST can help explain participation in digital platforms. BAS traits were strongly linked to the perception of multiple benefits and, through them, to positive attitudes and intentions. BIS traits had far weaker effects, indicating a need for trust-building and risk-reduction strategies when targeting these consumers.

By recognising these personality differences, platform managers can design more effective strategies to attract, engage, and retain users. The study also underscores the value of applying psychological theory to digital economy research, pointing the way for further work on how personality shapes behaviour in technology-mediated marketplaces.

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