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# The Cognitive Cost of Abundance: How Choice Overload and Decision Fatigue Drive Over-Ordering in Online Food Delivery

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# Abstract

This study aims to explore the relationship between perceived choice overload (CO) and over-ordering (OO), mediated by decision fatigue (DF), among online food delivery app (OFDA) users in South India. It further investigates the influence of price concern (PC) and leftover reuse intention (LRI) as control variables, and explores demographic differences in OO across age, gender, income, ordering frequency, living area, and family structure. It is a cross-sectional quantitative study with 330 food delivery app users across South India. Analysis was done using Confirmatory Factor Analysis (CFA) and Covariance-Based Structural Equation Modelling (CB-SEM) via AMOS. One-way ANOVA and independent samples t-test was used to test the demographic differences. Full mediation was found where CO strongly and significantly influenced DF which in turn significantly drove OO behaviour. PC significantly and negatively influenced OO, while LRI had no significant effect. Age and ordering frequency produced statistically significant differences in OO; while other demographic variables did not. This study is the first to construct and empirically validate a sequential cognitive process model connecting CO and OO through DF in the online food delivery context, integrating the Paradox of Choice and Ego Depletion Theory. Full mediation establishes DF as the mechanism underlying direct CO-OO associations previously reported in the literature. It further qualifies culturally-specific willpower-energising effect among Indians and establishes online food delivery as a theoretically distinct domain where DF amplifies rather than suppresses consumer behaviour. It contributes methodologically through CB-SEM with rigorous model fit reporting.


# INTRODUCTION

The online food delivery market in India has emerged to become one of fastest growing consumer technology markets. It is valued at USD 55.58 Billion in 2025 and is projected to expand at a CAGR of 22.18% through 2034, potentially reaching USD 337.15 Billion (IMARC, 2025). This exponential growth is supported by the convergence of structural forces in India. Underpinned by over 886 million internet users and 1.15 billion mobile subscribers (Nexdigm, 2025), app-based food ordering has scaled rapidly. With that scale, one of the food delivery platforms in India (Swiggy) alone handled more than 1.5 million food orders daily in 2024 (Kotak Neo Team, 2025; Straits Research, 2024). In this market context, South India had the largest regional market share of 39.6% of India's online food delivery market in 2024 (Social Samosa, 2025). In the Tier-1 cities of this region, around 70% of restaurant revenue is coming from online ordering now. It shows how deeply online food consumption has been rooted into daily urban lifestyle (Arora, 2025). Food delivery in South India is no longer used for convenience; it is has become a routine.

When the consumer enters these platforms, they are confronted with thousands of food choices (with multiple cuisines, price points, portion sizes, and customisation options) before they could even a single item is added to the cart. This in fact may represent a psychological burden despite the fact that having choice is considered to be empowering. The Paradox of Choice by psychologist Barry Schwartz (2004) proposes that the more options we have, the less satisfied we feel with our eventual decision. Having

many options theoretically increases freedom and the chances of finding the perfect product, but in practice leads to anxiety, paralysis, and dissatisfaction. In the context of food delivery apps, where consumers navigate highly dense menu options under the conditions of hunger, time pressure, etc., the consequences could extend beyond indecision. It might potentially lead to impulsive excessive ordering behaviour that neither serves the consumer's intent nor their wellbeing. When consumers purchase food quantities that exceed their actual consumption capacity, the surplus converts directly into plate waste and discarded leftovers (Zheng et al., 2023). Recent findings show consumer over-ordering (OO) as a direct and primary catalyst for the massive volumes of food waste generated across both traditional hospitality and online delivery sectors (Wang, Wang and Xing, 2025; Kohli et al., 2023). This is pressing because according to the UNEP Food Waste Index Report 2024, Indian households generate an estimated 55 kg of food waste per capita per year. While this is lower than the global average of 79 kg, India's huge population scales this up to roughly 78.2 million tonnes of household food waste annually.

On the other hand, the existing literature has not explored the cognitive mechanism connecting CO and OO behaviour. A wide range of antecedents including convenience, trust, price, value, service quality, and attitude has delved into previously for OO behaviour (Yeo et al., 2017; Sharma et al., 2021; Islam et al., 2024; Chiu et al., 2024). The literature remains heavily concentrated on adoption intention, satisfaction, and continuance, while cognitive and affective evaluations of the ordering experience itself remain significantly underexplored (Liu et al., 2024). More importantly, the role of choice overload (CO) as a cognitive stressor within the food delivery ecosystem has received very little attention. Also, the mediating role of decision fatigue (DF) has been virtually absent from the food delivery literature (Salathiyan et.al, 2025; Wang et.al, 2023).

This study pursues two objectives. First, to determine if there is a mediation relationship among perceived CO, DF and OO in South Indian OFDA consumers. Second, to check whether any sociodemographic variables influence the OO behaviour. The study also analyses data using Confirmatory Factor Analysis (CFA) and Covariance-Based Structural Equation Modelling (CB-SEM) via AMOS. Unlike Partial Least Squares SEM (PLS-SEM), which dominates the existing food delivery literature (Islam et al., 2024; Sharma et al., 2021; Talwar et al., 2021), CB-SEM works with maximum likelihood estimation and produces model fit indices (CFI, TLI, RMSEA, SRMR, $\chi^2/df$) that allow for a more rigorous assessment of how well the proposed model fits the observed data (Hair et al., 2013; Dash and Paul, 2021). The study is further anchored in two complementary theoretical frameworks of Paradox of Choice (Schwartz, 2004) and Ego Depletion Theory (Baumeister et al., 2024).

## LITERATURE REVIEW & RESEARCH FRAMEWORK

# Paradox of Choice

Individuals find difficult in juggling multiple choices. As the number of options increases, they are faced with conflict and they tend to postpone making decisions, seek more alternatives, or they abandon the idea of choosing an option altogether (Iyengar and Lepper, 2000). Schwartz (2004) posited that beyond a

threshold, variety of options produce anxiety and paralysis rather than well-being, supported by Scheibehenne et.al, (2010), Chernev et.al, (2014), Baum et.al, (2023). In the case of OFDAs where users juggle with hundreds of restaurants and menu options, CO is embedded in the platform design, positioning it as the independent variable and the cognitive stimulus in the study.

## Ego Depletion Theory

Ego depletion theory suggests that self-regulation depends on a finite energy resource named willpower, which depletes over time through acts of volition like choice, active response, and self-regulation (Baumeister et al., 2024; Pignatiello, Martin and Hickman, 2020). When willpower is exhausted, the mind loses its ability to maintain control and previously suppressed impulses are more likely to guide behaviour (Baumeister and Vohs, 2016). A meta-analysis confirmed ego depletion's effect on self-control and subjective fatigue (Hagger et al., 2010). Savani and Job (2017) showed that Indians believe that willpower is energizing rather than depleting, displaying a reverse effect of ego depletion where a second self-control task was performed better after an initial strenuous one. However, regardless of the cultural nuance, the sustained effort of working with an overwhelming OFDA interface constitutes prolonged self-regulation that decreases one's decision-making ability, which is defined in this study as DF, the proposed mediating mechanism. The originality of this study lies in integrating these frameworks in the food delivery space, constructing a sequential cognitive pathway from CO to OO, with DF being the mediating mechanism (Refer: Fig. 1).

## Choice Overload and Decision Fatigue (H1)

The relationship between CO and DF is based on the fundamental cognitive function of human decision-making. In OFDAs, this relationship operates with particular force. Studies have found that complex, multi-faceted choice environments (digital retail and Indian OTT), as seen in OFDAs, can consistently produce greater cognitive strain and decision difficulty (Jacob, Thomas and Joseph, 2024; Rajesh et al., 2025; Dar and Gul, 2024; Adriatico et al., 2022; Manolică et al., 2021). Boby (2024) and Özer Canarslan (2025) found significant relationships between perceived CO and decision paralysis among app users, leading to cart abandonment. Neurologically, sustained cognitive effort has been found to lead to the glutamate accumulation in the lateral prefrontal cortex (a region central to deliberate decision-making) which degrades its functioning and pushing individuals toward low-effort, short-term choices (Wiehler et al., 2022). Cumulatively, this evidence led to the following hypothesis:

*H1: CO positively influences DF among OFDA users.*

## Decision Fatigue and Over-Ordering (H2)

In buying decisions, studies have established that cognitive fatigue leads to stronger purchase urges and higher spending in unanticipated buying situations. Here, individuals tend to favour easier, less effortful

options over higher-value outcomes (Vohs and Faber, 2007; Steward, Looi and Chib, 2025). DF in general e-commerce contexts has been usually associated with cart abandonment, purchasing delays, and non-purchase outcomes (Salathiyan and Prathipa, 2025; Kim, 2021; Park and Yoon, 2022). However, the food delivery app context differs in two important ways that redirect the behavioural outcome from avoidance toward excess. First, food delivery app usage is mostly driven by hunger which can amplify impulsivity and present-biased decision-making (Skrynka and Vincent, 2019). Second, in general e-commerce context, abandonment has low-cost, whereas food delivery involves hunger that makes nonpurchase a physiologically uncomfortable option. This physiological urgency also redirects into low-deliberation ordering of multiple items.

This food-specific impulsivity mechanism is reinforced by further studies (Blain, Hollard and Pessiglione, 2016; Mullette-Gillman et.al 2015; Kovshova and Savchenko, 2023; Wang et.al, 2023; Brasington et al., 2025) where the fatigued decision making is driven by heuristics (relying on shortcuts and salient cues), immediate gratification and hedonic impulses. This is corroborated by Moon and Ji (2025) who found that fatigue significantly and negatively affected app loyalty while simultaneously increasing the likelihood of impulsive, unplanned ordering decisions. Furthermore, while variety enhances satisfaction up to a threshold, it simultaneously produces DF that impairs the quality of ordering decisions, compounding along with hunger (Dsouza et al., 2025). Taken together, this evidence led to the following hypothesis:

*H2: DF positively influences OO behaviour among OFDA users.*

## Choice Overload and Over-Ordering: The Direct Path (H3)

CO produces not only cognitive strain but also a set of behavioural coping responses to reduce the discomfort related with choosing under conditions of overwhelming options (Schwartz, 2004; Chernev et.al, 2014). One such coping response is the adoption of a regret-minimisation strategy. It refers to ordering multiple items simultaneously as a hedge against the anticipated regret of choosing wrongly (Chernev et.al, 2014; Jacob et.al, 2024). This is underpinned by heightened anxiety and decisional uncertainty, without cognitive fatigue mediating (Yuxin, 2024).

With respect to the food delivery app context, the abundance of menu options and perceived variety directly and positively influenced OO behaviour. Critically, this effect was observed through attitudinal and normative mechanisms that are conceptually distinct from cognitive depletion (Zheng et al., 2023; Kumala and Maizi, 2025). Park and Kang (2021) in their study also specifically examined fast-casual restaurant ordering and found that perceived CO directly reduced satisfaction with customisation and increased the tendency to add unnecessary items. This pattern is directly analogous to OO in digital food platforms. Misuraca et al. (2024) confirmed that large, complex assortments produce direct compensatory purchasing responses including over-selection particularly when decision-makers lack clear prior preferences and face time pressure. This body of evidence lead to the following hypothesis.

Testing this relationship is methodologically essential for determining whether mediation (H1 → H2) in this study is full or partial:

*H3: CO directly and positively influences OO behaviour among OFDA users.*

# Price Concern, Leftover Reuse Intention, and Over-Ordering (H4)

Price concern (PC) refers to the degree to which a consumer monitors and responds to monetary cost of food. Stancu et.al, (2016) established that price consciousness shapes food-waste reduction intentions primarily through two routes (planning routines & waste-reduction attitudes). In the online ordering context, Jia et.al, (2022) confirmed that strongly price-conscious consumers tend to gather information carefully before placing orders and are less prone to impulse-driven excess quantity choices; however, the relation is largely through perceived behavioral control and behavioral intention rather than through a direct reduction in order size. Taken together, these studies suggest that PC acts as a cognitive inhibitor on OO, even if the effect is indirect.

Leftover reuse intention (LRI), on the other hand, produces a more paradoxical relationship. Shankar et al. (2022) found that LRI was positively associated with OO, as some consumers deliberately over-order to use leftovers later. Talwar et al. (2022) similarly documented those subjective social norms around reuse influenced sustaining OO. Contrary to this, Permasih et.al, (2024) found that leftover reuse intention did not significantly reduce OO, indicating that the intention does not necessarily translate into behavioral restraint at the point of ordering.

*H4: There is a significant influence of PC and LRI on OO in OFDA.*

## Ordering Frequency and Over-Ordering (H5)

The number of times a consumer places orders (order frequency) through FDAs per week or month represents one of the most direct behavioral antecedents of OO documented in the literature. Jia et.al, (2022) found that food waste tended to be higher among consumers who ordered food online more frequently. Similarly, Talwar et al. (2022) found that habituated OO was more significant among frequent users whose ordering behaviour had become routine rather than deliberate. Based on this evidence, it is hypothesized that consumers who order more frequently from FDAs over-order to a significantly greater extent.

*H5: There is a significant difference in OO behaviour across different ordering frequencies.*

## Socio demographics and Over-Ordering (H6-H10)

The study also aims to determine if sociodemographic variables influence the OO behaviour. Giacomini, G. et al. (2024) reported that younger age was significantly and negatively associated with adhering to dietary plans and positively associated with impulsive buying behaviour. The study further examines whether gender (H7), income level (H8), living area (H9), and family structure (H10) influence OO behaviour. Prior literature presents mixed evidence across these variables (Jia et.al, 2022; Kilders et.al, 2023; Tonini et.al, 2023; Koivupuro et al., 2012; Grasso et al., 2019; Lima et al., 2024; Szakos, Szabó-Bódi, and Kasza, 2020) warranting empirical examination in the South Indian context.

*H6: There is a significant difference in OO behaviour across different age groups.*

*H7: There is a significant difference in OO behaviour between male and female respondents.*

*H8: There is a significant difference in OO behaviour across different income level groups.*

*H9: There is a significant difference in OO behaviour across different living area types (Urban, Semi-urban, Rural).*

*H10: There is a significant difference in OO behaviour across different family structure types (Nuclear, Blended, Extended).*

# METHODOLOGY

All construct measures used in this study were adapted and developed from established scales to suit the South Indian OFDA context. CO was measured using items adapted from Chernev, Böckenholt and Goodman (2014); DF from Hickman, Pignatiello and Tahir (2017); OO from Sharma et al. (2021), Talwar et al. (2022). A four-point Likert scale ranging from 1 (Strongly Disagree) to 4 (Strongly Agree) was used to record the responses. Participants based their responses on recent ordering experience. Full instrument with adapted items is provided in the supplementary material. Data were collected using an online survey distributed to online food delivery app users across the five states in South India. The convenience and snowball sampling methods were employed to capture the responses of active OFDA users and constraints of reaching respondents across multiple states. Participants were screened at the beginning of the survey to confirm recent OFDA usage and were asked to answer based on the most recent high-choice ordering experience. Ethical clearance was obtained from the Ethical Review Board of Amrita School of Business, Coimbatore. Informed consent was also obtained from the 330 respondents. The demographic profile of the respondents is presented in Table 2. The sample was predominantly male (53%) with female respondents constituting 47%. A significant portion of the sample belonged to the 18–25 age group (see Table II). Generation Z adults (aged 18–29) demonstrate the highest adoption rates of online food delivery platforms globally, ordering at a rate approximately six times higher than senior consumers (Bennett et al., 2025). In India specifically, they drive over 40% of the country's online food economy and constitutes the primary active user base of Swiggy and Zomato (The Hindu Bureau, 2024). This justifies the non-probability sampling method and the notable the skew toward the 18–25 age cohort (63.9% of the sample).

Table I: Demographic Profile of Respondents

| Characteristic | Category | N | % |
|---|---|---|---|
| Gender | Male | 175 | 53 |
| | Female | 155 | 47 |
| Age Group | 18–25 | 211 | 63.9 |
| | 26–35 | 45 | 13.6 |
| | 36–45 | 35 | 10.6 |
| | 46–55 | 22 | 6.7 |
| | 56+ | 17 | 5.2 |
| Living Area | Urban | 203 | 61.5 |
| | Semi-urban | 88 | 26.7 |
| | Rural | 39 | 11.8 |
| Order Frequency | Multiple times a week | 34 | 10.3 |
| | Once a week | 65 | 19.7 |
| | 2–3 times a month | 100 | 30.3 |
| | Once a month or less | 78 | 23.6 |
| | Rarely / Only on special occasions | 53 | 16.1 |
| Family Annual Income | Below ₹3 Lakhs | 92 | 27.9 |
| | ₹3- ₹6 Lakhs | 59 | 17.9 |
| | ₹6- ₹12 Lakhs | 93 | 28.2 |
| | ₹12- ₹24 Lakhs | 58 | 17.6 |
| | Above ₹24 Lakhs | 28 | 8.5 |
| Family Structure | Nuclear | 263 | 79.7 |
| | Blended | 52 | 15.8 |
| | Extended | 15 | 4.5 |
| Source(s): Author’s work | | | |

# RESULTS

The measurement model was evaluated through Confirmatory Factor Analysis (CFA) using AMOS prior to structural model testing. The model demonstrated acceptable fit: $\chi^2/df = 1.550$, CFI = 0.974, TLI = 0.966, RMSEA = 0.041 (90% CI: 0.023–0.057, PCLOSE = 0.817), all meeting the thresholds recommended for CB-SEM (Hair et al., 2013; Hu and Bentler, 1999).

Table II: Measurement Model - Factor Loadings, Reliability, and Validity.

| Construct | Item | Std. Loading (λ) | $R^2$ | Cronbach's α | CR | AVE |
|---|---|---|---|---|---|---|
| Choice Overload | CO1 | 0.77 | 0.594 | 0.745 | 0.84 | 0.568 |
| | CO2 | 0.757 | 0.574 | | | |
| | CO3 | 0.768 | 0.589 | | | |
| | CO4 | 0.718 | 0.515 | | | |
| Decision Fatigue | DF1 | 0.849 | 0.721 | 0.771 | 0.869 | 0.688 |
| | DF2 | 0.842 | 0.708 | | | |
| | DF3 | 0.797 | 0.635 | | | |
| Over-Ordering | OO1 | 0.782 | 0.612 | 0.813 | 0.877 | 0.642 |
| | OO2 | 0.798 | 0.637 | | | |
| | OO3 | 0.776 | 0.602 | | | |
| | OO4 | 0.846 | 0.716 | | | |
| **Source(s): Author's work** | | | | | | |

*All loadings significant at $p < 0.001$. CR = Composite Reliability; AVE = Average Variance Extracted.*

All standardised factor loadings exceeded the recommended threshold of 0.70 (Hair et al., 2013), ranging from 0.718 to 0.849 across the three constructs (see Table II), and were statistically significant at $p < 0.001$, confirming that all items relate meaningfully to their respective latent constructs. Reliability was confirmed with all Cronbach's alpha and CR values exceeding 0.70 (Fornell & Larcker, 1981) (see Table II). AVE values were 0.568 for CO, 0.688 for DF, and 0.642 for OO (see Table II), all surpassing the minimum criterion of 0.50 (Fornell & Larcker, 1981), indicating that each construct explains the majority of the variance in its indicators, confirming their convergent validity.

Table III: Discriminant Validity - Fornell-Larcker Criterion and HTMT Ratios.

| Construct | CO | DF | OO |
|---|---|---|---|
| Choice Overload (CO) | **0.754** | 0.804 | 0.441 |
| Decision Fatigue (DF) | 0.61 | **0.829** | 0.578 |
| Over-Ordering (OO) | 0.345 | 0.458 | **0.801** |
| **Source(s): Author's work** | | | |

*Diagonal elements (bold) = square root of AVE. Below diagonal = inter-construct correlations (Fornell-Larcker criterion). Above diagonal = HTMT ratios. All HTMT values < 0.90 threshold (*Henseler, Ringle and Sarstedt, 2014*), confirming discriminant validity.*

Discriminant validity was confirmed via both the Fornell-Larcker criterion and HTMT ratios (all < 0.90; Henseler, Ringle and Sarstedt, 2014) (see Table III). Taken together, the measurement model demonstrates robust psychometric properties, establishing a reliable base for structural model analysis. The common method bias (CMB) was tested using Harman's single factor test across all eleven measurement items spanning the three constructs. The first factor explained only 40.45% of the total variance, which is below the accepted limit of 50% (Podsakoff et al., 2003), confirming that common method bias does not pose a significant threat to the validity of the findings in this study.

The structural model was tested using a bootstrapping procedure with 5,000 resamples, following the bias-corrected percentile method recommended for mediation analysis (Preacher and Hayes, 2008).

**H1** — which proposed that CO positively influences DF — was strongly supported (β = 0.798, B = 0.808, SE = 0.098, CR = 8.213, p < 0.001; 95% BC CI [0.694, 0.889]). **H2** — proposing that DF positively influences OO — was also confirmed (β = 0.606, B = 0.858, SE = 0.208, CR = 4.127, p < 0.001; 95% BC CI [0.300, 0.959]). **H3** — the direct effect of CO on OO — was not supported (β = -0.043, B = -0.062, SE = 0.202, CR = -0.308, p = 0.758; 95% BC CI [-0.411, 0.252]), indicating that CO does not exert a significant direct effect on OO when DF is present in the model (see Table IV).

Regarding the control variable tested in **H4**, PC exerted a significant negative effect on OO (β = -0.143, B = -0.313, SE = 0.116, CR = -2.693, p = 0.007; 95% BC CI [-0.238, -0.042]), indicating that more price-sensitive consumers are significantly less likely to OO. LRI did not significantly (p = 0.908) influence OO and was therefore excluded from the final model.

Table IV: Structural Model Results.

| Hypothesis | Path | β | B | SE | CR | p | 95% BC CI | Result |
|---|---|---|---|---|---|---|---|---|
| H1 | CO → DF | 0.798 | 0.808 | 0.098 | 8.213 | *** | [0.694, 0.889] | Supported |
| H2 | DF → OO | 0.606 | 0.858 | 0.208 | 4.127 | *** | [0.300, 0.959] | Supported |
| H3 | CO → OO (direct) | -0.043 | -0.062 | 0.202 | -0.308 | 0.758 | [-0.411, 0.252] | Not Supported |
| H4a | PC → OO | -0.143 | -0.313 | 0.116 | -2.693 | 0.007 | [-0.238, -0.042] | Supported |
| H4b | LRI→ OO | 0.006 | 0.009 | 0.076 | 0.116 | 0.908 | [-0.099, 0.116] | Not Supported |
| **Source(s): Author's work** | | | | | | | | |

*β = standardised coefficient; B = unstandardised coefficient; SE = standard error; CR = critical ratio. *** p < 0.001. BC CI = bias-corrected bootstrap confidence interval (5,000 resamples).*

# Mediation Analysis

The standardised indirect effect of CO on OO through DF was 0.484 (unstandardised indirect effect = 0.693, SE = 0.150; 95% BC CI [0.250, 0.850], p < 0.001). Since the bootstrap confidence interval does not include zero, the indirect effect is statistically significant, confirming that DF mediates the relationship between CO and OO. Furthermore, the direct path from CO to OO was non-significant (β = -0.043, p = 0.759) when the mediator was included in the model, while the indirect path remained highly significant (Refer Fig. 2).

This confirms **full mediation** (Preacher and Hayes, 2008). Age group significantly influenced OO behaviour (F = 2.571, p = 0.027), with younger respondents reporting higher OO tendencies. Ordering frequency also produced a significant difference (F = 4.224, p = 0.002), with more frequent app users reporting significantly higher OO. Gender, income level, living area, and family structure did not produce statistically significant differences in OO behaviour (see Table V).

Table V: Demographic Comparative Analysis for Over-Ordering.

| Group | Test | F/t statistic | p-value | Result |
|---|---|---|---|---|
| Age | One-way ANOVA | 2.571 | 0.027* | Significant |
| Order Frequency | One-way ANOVA | 4.224 | 0.002** | Significant |
| Gender | Independent samples t-test | -0.536 | 0.592 | Not Significant |
| Income Level | One-way ANOVA | 0.86 | 0.488 | Not Significant |
| Living Area | One-way ANOVA | 0.005 | 0.995 | Not Significant |
| Family Structure | One-way ANOVA | 1.235 | 0.292 | Not Significant |
| | **Source(s): Author's work** | | | |

** p < 0.05; ** p < 0.01.*

# DISCUSSION

## Choice Overload and Decision Fatigue (H1 — Supported)

The results confirmed (H1) that CO positively influences DF among food delivery app users strongly, indicating that nearly 80% of the variance in DF is attributable to perceived CO. It shows that more options or varieties does not liberate consumers but instead increases their cognitive burden. This burden is structurally embedded in the digital platform experience with its excessive size and complexity of choice set (Schwartz, 2004; Chernev, Böckenholt and Goodman, 2014; Abell, Biswas and Mera, 2024; Moon and Ji, 2025; Dar and Gul, 2024).

## Decision Fatigue and Over-Ordering (H2 — Supported)

H2 was confirmed establishing DF as a significant and substantial driver of OO in the OFDA context. It could be because those fatigued individuals exhibited stronger urges to purchase and actually spent significantly more than non-depleted counterparts (Vohs and Faber, 2007). The depleted self-control specifically increases the likelihood of impulsive and indulgent food selections (Brasington et al., 2025). Hunger could also cause the fatigue-driven impulsivity toward excessive ordering rather than avoidance. Although Savani and Job (2017) documented a willpower-energising effect in Indian cultural contexts, this was observed in controlled lab tasks. Navigating OFDAs can induce sustained, high-complexity cognitive effort that produces neurobiological fatigue through glutamate accumulation in the prefrontal cortex (Wiehler et al., 2022; Salathiyan and Prathipa, 2025; Pessiglione et al., 2025; Steward et.al, 2025). This biological process could transcend cultural conditioning.

## Direct Effect of Choice Overload on Over-Ordering (H3 — Not Supported)

H3 was not supported as the direct path between CO and OO was statistically non-significant and negligibly small in magnitude. This non-significance contradicts the findings of Zheng et al. (2023), Boby

(2024), and Kumala and Maizi (2025). However, on the other hand, it advances the theory meaningfully as it explains that CO does not independently drive OO, but does so by first depleting their decision-making capacity. This result, cumulated with the significant mediated pathway, indicates **full mediation**. DF fully accounts for the relationship between CO and OO, with no residual direct effect remaining.

## Price Concern and Leftover Reuse Intention as Controls (H4 — Partially Supported)

H4 examined the influence of PC and LRI on OO as control variables. PC was found to exert a significant negative effect on OO, confirming that price-sensitive consumers are meaningfully less likely to OO. This finding aligns with the broader consumer behaviour literature that established price consciousness as a moderating influence on excessive purchasing (Chernev, Böckenholt and Goodman, 2014; Dar and Gul, 2024).

LRI, however, did not significantly influence OO behaviour. This contrasts with the assumption in some prior literature that consumers who intend to reuse leftovers may not hesitate to order more than needed (Shankar et al., 2022; Talwar et al., 2021). The non-significant result warrants future research to find if leftover reuse intentions are decoupled from the ordering decision itself in South Indian cultural pattern.

## Ordering Frequency, Age and Over-Ordering (H5 & H6 — Supported)

H5 & H6 were confirmed with significant differences in OO across ordering frequency groups and different age cohorts. This is theoretically coherent where consumers who order more frequently tend to accumulate the exposure to the food delivery apps' CO environment and they are repeatedly subjected to the fatiguing stimulus. Furthermore, habitual frequent orders may develop routinised OO behaviours and this may persist even in the absence of acute DF (Wang, Mo and Ho, 2023; Kovshova and Savchenko, 2023). The result is also consistent with Boby (2024) and Jia, Zhang and Qiao (2022) findings that younger app users are particularly vulnerable to CO and its behavioural consequences, and they are associated with higher food waste generation in online ordering contexts. In the South Indian sample, younger consumers appear to over-order more than older age groups. This may also reflect generational differences in price sensitivity, conforming with norms around food waste, and familiarity with app-based ordering heuristics.

## Gender, Income, Living Area, and Family Structure (H7–H10 — Not Supported)

The non-significance of gender, income level, living area, and family structure in shaping OO behaviour in the present study could have theoretical meaning. It suggests that the overload-fatigue-over-ordering pathway, once activated by the food delivery app interface, operates as a universal cognitive mechanism that transcends demographic boundaries. It is as suggested by Pessiglione et al. (2025) where the neurobiology can override individual differences. This interpretation aligns with Bennett et al.'s (2025)

large-scale multi-country analysis, which found that while demographic variables shaped platform adoption patterns, they did not consistently differentiate the intensity of cognitive engagement once inside the platform.

# THEORETICAL CONTRIBUTIONS & IMPLICATION OF THE STUDY

The present study makes five theoretical contributions to the literature on consumer behaviour in online food delivery apps. First, this study proposes and empirically validates for the first time a sequential cognitive process model that links CO, DF, and OO behaviour in the context of online food delivery applications. Initially, only attitudes and convenience (Islam et al., 2024; Sharma et al., 2021) were explored in relation to OO. Second, this study achieves the novel integration of two frameworks: the Paradox of Choice (Schwartz, 2004) and Ego Depletion Theory (Baumeister et al., 2024) within the online food delivery space. Third, the discovery of full mediation, indicating that CO affects OO solely through DF, without any significant residual effect is theoretically important. Prior studies that found direct associations between choice-related variables and over-ordering (Zheng et al., 2023; Boby, 2024; Kumala and Maizi, 2025) can now be reinterpreted as cognitive-mechanism-mediated effects. This reframing is responsible for establishing DF as the intermediate cognitive state that facilitates overload-induced behaviour. Fourth, despite Savani and Job's (2017) willpower-energizing effect among Indians, standard depletion operated fully here, suggesting neurobiological fatigue (Wiehler et al., 2022) transcends cultural conditioning. Fifth, unlike general e-commerce where DF causes abandonment (Kim, 2021; Park and Yoon, 2022), hunger redirects depletion toward excess, establishing DF as a context-sensitive amplifier rather than a uniform behavioral suppressor.

The results of this study have significant actionable implications for different stakeholders in the online food delivery space. The full mediation finding of decision fatigue is an outcome that is noteworthy to platform designers. They must prioritize reducing the cognitive effort per session through personalization and expandable interfaces. They could leverage the price concern by showing check-out review prompts to customers before they pay. Reimagining digital menu design with sub-categories and portion size information is a way by which restaurant operators can contribute to cognitive welfare and reduce decision fatigue. The results show that awareness interventions will be effective across all user groups. For the information of policymakers and public health authorities, regulatory frameworks which insist on implementing mindful choice architecture (like friction points and waste-impact notifications) could help reduce the cognitive overload.

# LIMITATIONS AND FUTURE RESEARCH

The current study acknowledges several limitations, and these provide a clear path for future research. Firstly, the use of a cross-sectional survey design only registers the perceptions and behaviours at one snapshot of time and cannot lend itself to establish causal directionality provided by experimental or longitudinal designs. Secondly, the study is limited to South Indian online food delivery app users. It is of notice that the theoretical model developed in this study has the potential to be tested in cross-cultural

and cross-market applications. However, the contextual differences are present: European food delivery interfaces (valued at USD 376 billion in 2024) typically present fewer cuisine categories than their South Indian counterparts. The average portion sizes differ significantly, and consumer price sensitivity patterns vary across income groups in ways that may moderate the strength of the overload-fatigue pathway (Market Data Forecast, 2025). Third, the study does not include moderating variables that could explain and shape the strength of the relationships. Fourth, the non-significance of LRI is a finding that requires further exploration. Fifth, while age and ordering frequencies had significant effects, the absence of effects for gender, income, living area, and family structure in this sample does not indicate a universal absence of these effects.

## CONCLUSION

The proliferation and adoption of online food delivery apps in South India has resulted in an environment filled with an abundance of choice carries a cognitive cost that moves beyond customer satisfaction and results in excessive, wasteful ordering behaviour. Grounded in the theoretical integration of the Paradox of Choice (Schwartz, 2004) and Ego Depletion Theory (Baumeister et al., 2024), the findings confirm that CO strongly induces DF (β = 0.798), which drives OO (β = 0.605). Full mediation is also established. PC limit OO, which age and ordering frequency turn out to be significant differentiators. Theoretically, the study offers the first empirical validation of a dual-theory cognitive process model linking CO to OO through DF. Practically, platform designers can intervene by reducing the cognitive effort through personalization coupled with mindful design while policymakers enforce accountability.

## Declarations

# Author contributions Statement:

Conceptualization: M. Sathish, Thilak Srikannan, Niveda Anoop; Validation: M. Sathish, Thilak Srikannan, Niveda Anoop and KP Naachimuthu; Formal analysis: Thilak Srikannan, Niveda Anoop and M Sathish; Data Curation: Thilak Srikannan, Niveda Anoop and M Sathish; Writing: Thilak Srikannan, Niveda Anoop, M. Sathish, KP Naachimuthu; Review and Editing: Thilak Srikannan, Niveda Anoop, M. Sathish, KP Naachimuthu. All authors have read and agreed to publish the manuscript

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# Data Availability

The anonymized raw data set is available as Responses.xlsx. Coding scheme is available as Coding_Sheet.docx. Processed data is available as proceed_data.xlsx. These files compressed and uploaded as supplementary_files.zip

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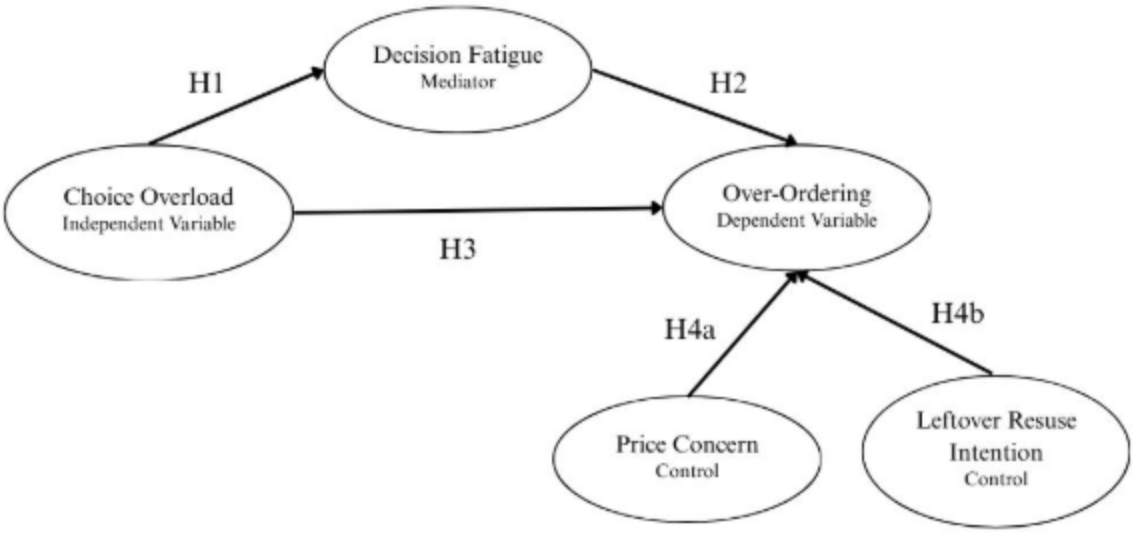
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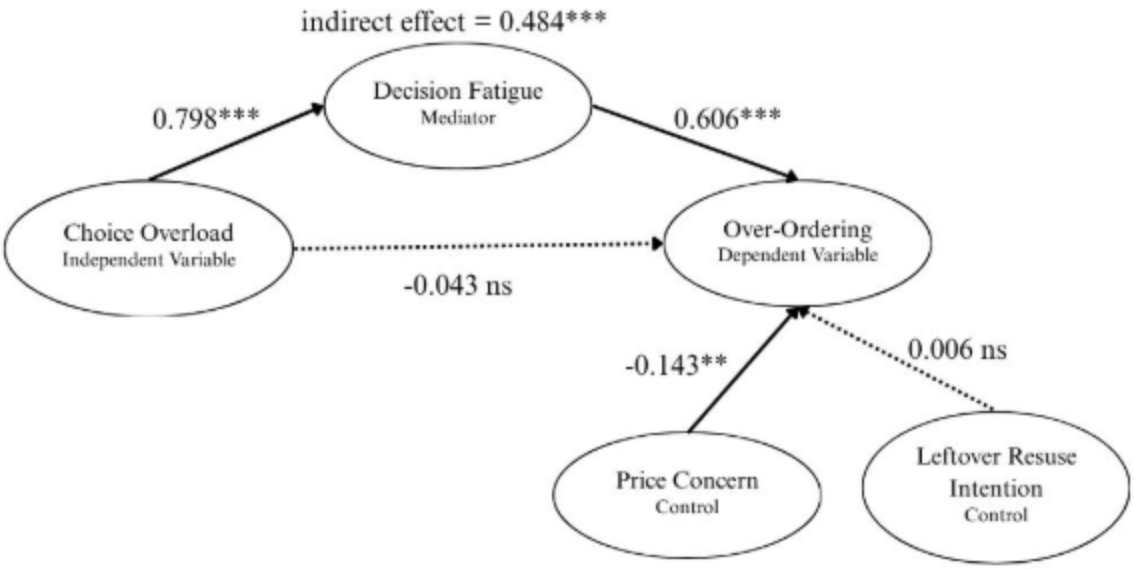
# Figures




*Source(s): Author's work*

**Figure 1**

Conceptual Diagram




*Source(s): Author's work*

**Figure 2**

Model Output Diagram

# Supplementary Files

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