The Influence of Digital Wallet Notifications on Spending Behaviour

1.Mr.Sigirisetty Venkata Mohith Vikash, 2.Dr.V.Madhulatha

1. Research Scholar-BBA,KLEF, sigirisettymohith@gmail.com

2.Professor, KL Business school, Koneru Lakshmaiah Education Foundation,

Abstract

Digital wallets have become a primary payment channel for consumers, and the push notifications they send, such as cashback alerts, promotional offers, payment reminders and transaction confirmations, are a constant feature of the payment experience. This study examines whether and how these notifications influence spending behaviour. Using a cross-sectional survey design with a sample of 300 digital wallet users, three hypotheses were tested with Excel-based statistical procedures. A chi-square test of independence examined whether notification frequency is associated with impulse purchasing; a one-way ANOVA compared monthly wallet spending across the dominant type of notification received; and a multiple linear regression estimated the effect of daily notification volume on monthly spending after controlling for age, income and notification engagement. Impulse purchasing rose sharply with notification frequency (14.0% at low, 30.9% at medium and 51.4% at high frequency; $\chi^2(2) = 23.49$, $p < .001$, Cramér's $V = .28$). Mean monthly spending differed significantly by notification type, $F(3, 296) = 16.67$, $p < .001$, $\eta^2 = .145$, with cashback/offer and promotional notifications associated with the highest spending and payment reminders with the lowest. In the regression model ($R^2 = .533$), each additional daily notification was associated with about ₹332 more monthly spending ($p < .001$), alongside significant effects of income and engagement. The findings suggest that notifications function as behavioural nudges whose effect depends on both their volume and their content. Implications for wallet providers, regulators and consumers are discussed, together with limitations and directions for future research.

Keywords: digital wallet; push notifications; spending behaviour; impulse buying; nudge; UPI; consumer behaviour

1. Introduction

Mobile payments have moved from a novelty to an everyday habit. In India, the growth of the Unified Payments Interface (UPI) and app-based wallets has placed a payment instrument on almost every smartphone, and the same pattern of rapid adoption can be observed in many other economies. Alongside the convenience of a one-tap payment, wallet applications communicate with users through a steady stream of push notifications: confirmation of a successful transaction, a reminder that a bill is due, a scratch card or cashback offer, or a limited-time promotion from a partner merchant. Unlike email or in-store advertising, a notification reaches the user at the moment they hold the payment device, which shortens the distance between an impulse and a purchase.

This makes notifications behaviourally interesting. Behavioural economics has long argued that small changes in the choice environment, or 'nudges', can alter decisions without changing the available options or their prices (Thaler & Sunstein, 2008). Payment research shows that the way money is paid, for example by card rather than cash, changes how much consumers spend because it reduces the salience of the 'pain of paying' (Prelec & Loewenstein, 1998; Soman, 2001; Raghubir & Srivastava, 2008). If the payment interface itself shapes spending, then the messages delivered through that interface are plausible candidates for doing the same.

Despite the practical importance of the question, relatively little empirical work links the characteristics of digital wallet notifications (how often they arrive and what they say) to measurable spending outcomes. Most industry commentary focuses on engagement metrics such as open rates, rather than on whether notifications change how much consumers spend or whether they trigger unplanned purchases. This study addresses that gap.

1.1 Research objectives

- To assess whether the frequency of wallet notifications is associated with impulse purchasing.
- To test whether average monthly wallet spending differs according to the dominant type of notification users receive.

- To estimate the effect of daily notification volume on monthly spending while controlling for age, income and notification engagement.

1.2 Contribution

The study contributes a transparent, replicable analysis that uses three complementary techniques (categorical association, group comparison and multivariate regression) on the same dataset, and provides a spreadsheet implementation that practitioners and students can reuse with their own data.

2. Literature Review and Hypotheses

2.1 Payment mechanisms and the pain of paying

Mental accounting research suggests that consumers track spending and its costs imperfectly and that payment format changes the psychological cost of a purchase (Thaler, 1985). Prelec and Loewenstein (1998) proposed that the 'pain of paying' is weakened when payment is decoupled from consumption, a view supported by experimental evidence that credit cards and other non-cash methods increase willingness to pay and spending (Soman, 2001; Raghubir & Srivastava, 2008). Digital wallets are an extreme case of decoupling: payment is a fingerprint or a tap, and the amount leaves an account that the user may not see. Notifications add a second layer, because they decide what information about money is made salient, and when.

2.2 Impulse buying

Impulse buying is an unplanned purchase characterised by a sudden, often powerful urge to buy immediately (Rook, 1987). Beatty and Ferrell (1998) showed that impulse buying is shaped by both the individual's traits and situational cues such as time and money available. Time-inconsistent preferences offer a further explanation: when a tempting offer is presented immediately, present-biased consumers give in more readily than they would in a planned decision (Hoch & Loewenstein, 1991). A cashback banner that appears the moment a user opens the app is exactly this kind of cue. The more often such cues arrive, the more opportunities there are for an impulse to be triggered, which motivates the first hypothesis.

2.3 Persuasive technology and notification content

Fogg's (2009) behaviour model holds that behaviour occurs when motivation, ability and a prompt converge. A mobile notification is a near-perfect prompt, and a wallet makes the ability to act (paying) almost effortless. Notifications, however, are not homogeneous. Transaction alerts and payment reminders are informational, and they may even encourage reflection or budgeting. Cashback and promotional messages are persuasive, offering a reward that increases perceived value. Research on technology acceptance suggests that perceived usefulness and ease of use shape how people respond to technology features (Davis, 1989; Venkatesh et al., 2003); in the wallet setting, notifications perceived as useful and rewarding are more likely to be acted on. We therefore expect spending to differ by notification type.

2.4 Control variables

Spending capacity depends on income, and consumer research routinely finds that younger consumers are more receptive to app-based promotions. Engagement, meaning the extent to which a user reads and acts on notifications, determines whether exposure translates into behaviour. These variables are included as controls so that the effect of notification volume is not confounded by who receives many notifications.

2.5 Hypotheses

- **H1:** Notification frequency (low, medium, high) is significantly associated with impulse purchasing (Yes/No).
- **H2:** Mean monthly wallet spending differs significantly across the dominant type of notification received.
- **H3:** The number of notifications received per day positively predicts monthly wallet spending after controlling for age, income and engagement.
- **H4 (supplementary):** Age group is significantly associated with impulse purchasing.

3. Research Methodology

3.1 Research design

The study uses a quantitative, cross-sectional, survey-based design. Self-reported data were collected on notification exposure and on spending in the previous month, and were analysed using Microsoft Excel.

3.2 Population, sample and data

The target population is adult (18+) active users of at least one digital wallet or UPI application. A sample of 300 respondents was analysed, which comfortably exceeds the minimum needed for a four-predictor regression (commonly 10–20 observations per predictor) and satisfies the expected-count requirements of the chi-square test for most cells. For the present draft, the responses are simulated (see the data note on page 1) with parameters chosen to resemble a plausible urban Indian user base. In a live study, a non-probability convenience or snowball sample distributed through online channels would be typical, and this should be acknowledged as a limitation.

3.3 Variables and measurement

Variable	Measurement	Role / Test
Notifications per day	Self-reported average count (numeric)	Predictor (H3); categorised for H1
Notification frequency	Low ≤ 5; Medium 6–10; High > 10 per day	Categorical IV (H1)
Dominant notification type	Cashback/Offer; Transaction Alert; Payment Reminder; Promotional	Factor (H2)
Impulse purchase	Yes/No: made an unplanned purchase after a wallet notification in the past month	Categorical DV (H1, H4)
Monthly wallet spend	Self-reported amount spent through wallet(s) in INR	Continuous DV (H2, H3)
Engagement score	Mean of Likert items (1–5) on reading and acting on notifications	Predictor / control (H3)
Age, income	Age in years; monthly income in INR ’000	Controls (H3); age group for H4

Table 1. Variables, measurement and role in the analysis.

3.4 Statistical procedures

All analyses were implemented with live Excel formulas in the accompanying workbook and cross-checked against an independent calculation in Python (results were identical to the reported precision). The significance level was $\alpha = .05$.

- **Chi-square test of independence** (H1, H4): observed counts from COUNTIFS; expected counts = (row total × column total) / N; $\chi^2 = \Sigma(O - E)^2/E$; p from CHIDIST; effect size Cramér’s V.
- **One-way ANOVA** (H2): between- and within-group sums of squares computed from group means; F = MS-between / MS-within; p from FDIST; effect size η^2. Because ANOVA is omnibus, Bonferroni-adjusted pairwise t-tests (using pooled mean square error) identify which groups differ.
- **Multiple linear regression** (H3): ordinary least squares via LINEST, with standard errors, t-tests, 95% confidence intervals, R^2, adjusted R^2, overall F and standardised coefficients.

3.5 Assumptions

For the chi-square tests, no more than 20% of cells should have expected counts below 5 and none below 1. For ANOVA, the largest-to-smallest standard deviation ratio was 1.10 (Levene’s test: $p = .970$), supporting homogeneity of variance.

For the regression, variance inflation factors ranged from 1.02 to 1.07 (no multicollinearity concern), and the residuals did not depart from normality (Shapiro–Wilk $W = .994$, $p = .280$). Observations are assumed independent, as each respondent contributes one record.

4. Data Analysis and Results

4.1 Descriptive statistics

The sample was 50.0% female, 47.0% male and 3.0% other. Half of the respondents (49.3%) were aged 25–34, and a further 28.0% were aged 18–24. Respondents received an average of 9.12 notifications per day ($SD = 3.81$) and spent ₹9,311.90 ($SD = 2,672.69$) per month through digital wallets. Overall, 35.7% (107 of 300) reported at least one impulse purchase after a notification. The most common dominant notification type was Transaction Alert (33.7%), followed by Cashback/Offer (28.3%), Promotional (23.0%) and Payment Reminder (15.0%).

Table 2. Descriptive statistics of continuous variables (N = 300)

Variable	Mean	SD	Min	Median	Max
Age (years)	29.41	7.90	18	29	56
Monthly income (₹ ’000)	39.78	21.97	9	36	179
Notifications per day	9.12	3.81	1	9	21
Engagement score (1–5)	2.95	0.79	1.0	3.0	5.0
Monthly wallet spend (₹)	9,311.90	2,672.69	2,250	9,230	18,730

4.2 Chi-square test: notification frequency and impulse purchasing (H1)

Table 3 cross-tabulates notification frequency with impulse purchasing. The share of respondents who made an impulse purchase increased steadily with frequency, from 14.0% in the low group to 30.9% in the medium group and 51.4% in the high group (Figure 1). The association was statistically significant, $\chi^2(2, N = 300) = 23.49$, $p < .001$. All expected counts exceeded 5 (minimum = 17.83). Cramér’s $V = .28$ indicates a small-to-medium effect. H1 is therefore supported.

Table 3. Notification frequency by impulse purchase (observed counts, row %)

Notification frequency	Impulse: Yes	Impulse: No	Total	Yes (%)
Low (≤ 5 per day)	7	43	50	14.0%
Medium (6–10)	43	96	139	30.9%
High (> 10)	57	54	111	51.4%
Total	107	193	300	35.7%

Note. $\chi^2(2) = 23.49$, $p < .001$, Cramér’s $V = .28$.

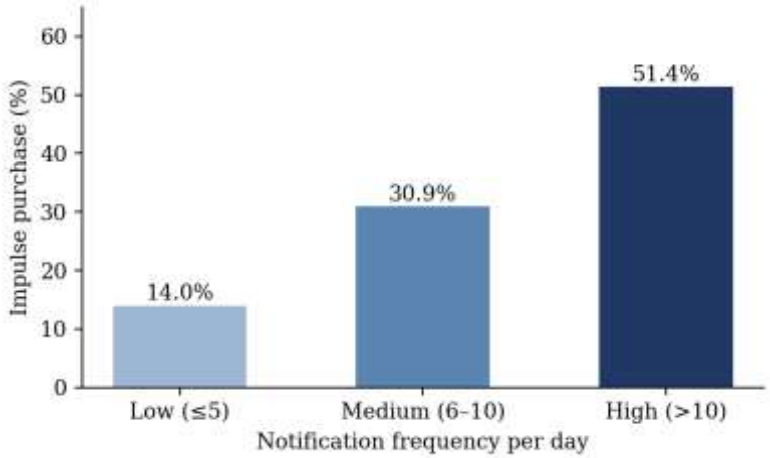


Figure 1. Impulse purchase rate by notification frequency.

Supplementary test (H4). Age group and impulse purchasing were not significantly associated, $\chi^2(3, N = 300) = 5.59$, $p = .133$, $V = .14$. Impulse rates were 44.0% (18–24), 32.4% (25–34), 36.4% (35–44) and 15.4% (45+). One of the eight cells (12.5%) had an expected count slightly below 5 (4.64, for the 45+ group), which is within the accepted tolerance, but the small 45+ subgroup ($n = 13$) means this result should be interpreted cautiously. H4 is not supported.

4.3 One-way ANOVA: spending by notification type (H2)

Table 4 shows that mean monthly spending was highest among users whose dominant notification type was Promotional (₹10,300.00) or Cashback/Offer (₹10,158.59), lower for Transaction Alerts (₹8,726.24), and lowest for Payment Reminders (₹7,512.00). The omnibus test was significant, $F(3, 296) = 16.67$, $p < .001$, with $\eta^2 = .145$, a large effect: roughly 14.5% of the variance in spending is associated with notification type. H2 is supported.

Table 4. Monthly wallet spend (₹) by dominant notification type

Notification type	n	Mean	SD	Rank by mean
Cashback/Offer	85	10,158.59	2,487.01	2
Promotional	69	10,300.00	2,516.61	1
Transaction Alert	101	8,726.24	2,394.92	3
Payment Reminder	45	7,512.00	2,625.56	4

Table 5. ANOVA summary

Source	SS	df	MS	F	p
Between groups	308,729,296	3	102,909,765	16.67	< .001
Within groups	1,827,104,521	296	6,172,650		
Total	2,135,833,817	299			

Note. $\eta^2 = .145$. Levene's test: p = .970.

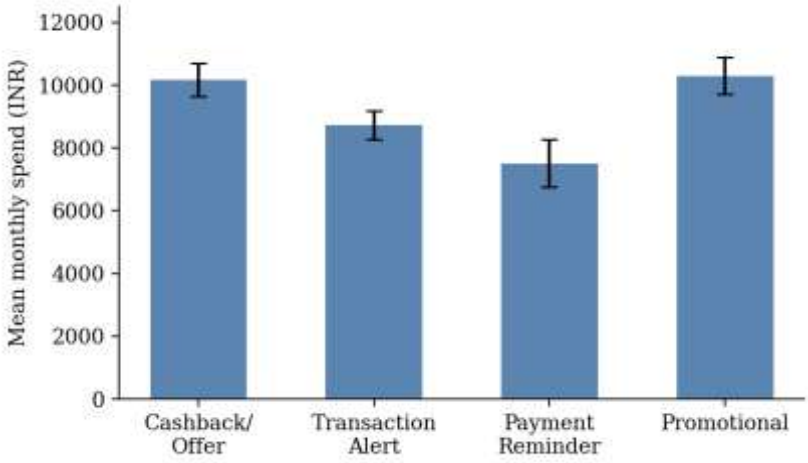


Figure 2. Mean monthly wallet spend by dominant notification type (error bars: 95% CI).

Bonferroni-adjusted pairwise comparisons (Table 6) show that Cashback/Offer and Promotional notifications do not differ from each other ($p = 1.00$), but both are associated with significantly higher spending than Transaction Alerts and Payment Reminders. Transaction Alerts are also associated with significantly higher spending than Payment Reminders ($p = .041$).

Table 6. Bonferroni-adjusted pairwise comparisons

Comparison	Mean diff (₹)	t	Adj. p	Sig.
Cashback vs Transaction Alert	1,432.35	3.92	< .001	Yes
Cashback vs Payment Reminder	2,646.59	5.78	< .001	Yes
Cashback vs Promotional	−141.41	−0.35	1.000	No
Transaction Alert vs Payment Reminder	1,214.24	2.73	= .041	Yes
Transaction Alert vs Promotional	−1,573.76	−4.06	< .001	Yes
Payment Reminder vs Promotional	−2,788.00	−5.86	< .001	Yes

4.4 Multiple linear regression: predictors of monthly spending (H3)

The regression model was significant, $F(4, 295) = 84.28$, $p < .001$, and explained 53.3% of the variance in monthly spending (adjusted $R^2 = .527$; standard error of estimate = ₹1,838.16). Notifications per day was a strong positive predictor ($b = 332.37$, $SE = 28.89$, $p < .001$): holding age, income and engagement constant, each additional daily notification was associated with about ₹332 more monthly spending (95% CI [275.52, 389.23]). Income ($b = 49.84$ per ₹1,000 of monthly income, $p < .001$) and engagement ($b = 1,152.89$ per scale point, $p < .001$) were also significant, whereas age was not ($p = .853$). Judging by standardised coefficients, notification volume ($\beta = .47$) was the strongest predictor, followed by income ($\beta = .41$) and engagement ($\beta = .34$). H3 is supported.

Table 7. Regression of monthly wallet spend (₹) on predictors

Predictor	b	SE	β	p	95% CI for b
Intercept	819.55	689.56	–	= .236	[−537.53, 2,176.63]
Age (years)	2.57	13.81	.008	= .853	[−24.61, 29.74]
Income (₹ '000)	49.84	4.88	.410	< .001	[40.23, 59.45]
Notifications per day	332.37	28.89	.474	< .001	[275.52, 389.23]
Engagement score	1,152.89	137.56	.342	< .001	[882.17, 1,423.61]

Note. $R^2 = .533$, adjusted $R^2 = .527$, $F(4, 295) = 84.28$, $p < .001$, $N = 300$.

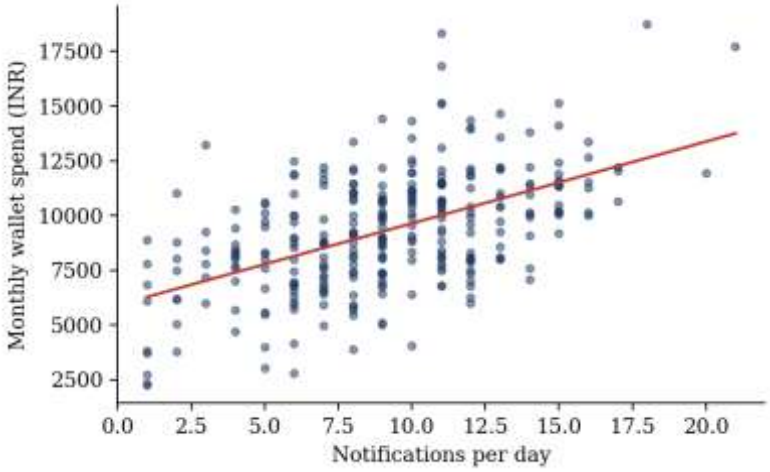


Figure 3. Monthly wallet spend against notifications per day, with fitted line (simple regression: slope = ₹373.44, R^2 = .283).

The fitted model is: Spend = 819.5 + 2.6(Age) + 49.8(Income) + 332.4(Notifications per day) + 1,152.9(Engagement). In the bivariate correlation matrix, notifications per day correlated r = .53 with spending, engagement r = .38 and income r = .37. The slope for notifications is larger in the simple regression (₹373) than in the multiple regression (₹332) because part of the simple association is shared with engagement, which rises with notification volume (r = .18).

4.5 Summary of hypothesis tests

	Hypothesis	Test and result	Decision
H1	Frequency and impulse purchase are associated	$\chi^2(2) = 23.49$, $p < .001$	Supported
H2	Spend differs by notification type	$F(3, 296) = 16.67$, $p < .001$	Supported
H3	Daily notifications positively predict spend	$b = 332.37$, $p < .001$	Supported
H4	Age group and impulse purchase are associated	$\chi^2(3) = 5.59$, $p = .133$	Not supported

Table 8. Summary of hypotheses.

5. Discussion

The three core tests converge on a single message: in this sample, digital wallet notifications are systematically related to how much consumers spend and how often they buy on impulse. The chi-square result shows a dose-response pattern, with the proportion of impulse purchasers more than tripling from low- to high-frequency users. This matches accounts in which repeated situational cues increase the chance that an urge to buy is triggered (Rook, 1987; Beatty & Ferrell, 1998) and in which immediate rewards overcome self-control (Hoch & Loewenstein, 1991).

The ANOVA results show that content matters as well as volume. Cashback and promotional notifications, which offer a reward, were associated with about ₹2,600–2,800 more monthly spending than payment reminders, whereas transaction alerts and payment reminders, which are informational and may prompt users to review their finances, were associated with lower spending. This is consistent with the view that informational messages increase the salience of money, partially restoring the 'pain of paying', whereas reward messages lower it (Prelec & Loewenstein, 1998; Soman, 2001). Fogg's (2009) model would interpret reward-based prompts as raising motivation at the very moment when ability is maximal.

The regression provides the most policy-relevant estimate: roughly ₹332 of additional monthly spending per additional daily notification, net of income, age and engagement. The significant engagement coefficient suggests that exposure alone is not sufficient, since notifications affect spending mainly when users pay attention to them. The absence of an age effect, once other variables are controlled, and the non-significant age-group association with impulse purchasing

(H4) indicate that susceptibility is driven more by exposure and engagement than by demographic group, although the small older subgroup limits the strength of this conclusion.

5.1 Causality and alternative explanations

The design is correlational. Users who spend more may simply have more transactions and therefore receive more transaction alerts, and users who like promotions may opt in to more notifications. Reverse causality and self-selection therefore cannot be excluded, and the coefficients should be read as associations rather than causal effects.

6. Implications

6.1 For wallet providers and merchants

- Notification volume has a measurable association with spending, which can be used to design campaigns; however, a strategy that maximises short-term spending may erode trust if users feel pressured.
- Reward-based notifications are associated with the highest spend; providers could pair them with spending summaries to support sustainable use.

6.2 For regulators and consumer-protection bodies

- Evidence of a dose-response relationship with impulse buying supports discussion of limits on promotional notification frequency, stronger opt-out controls and clearer labelling of marketing messages.

6.3 For consumers

- Users can reduce impulse exposure by muting promotional notifications while retaining transaction alerts and reminders, which are associated with lower spending.
- Setting a monthly budget alert in the wallet or bank app turns the notification channel into a self-control tool.

7. Limitations and Future Research

- **Simulated data.** The present results are generated from a simulated sample and must be replaced by real survey data before any substantive claim is made.
- **Self-report and recall bias.** Notification counts and spending are self-reported; wallet logs or screen-time data would be more accurate.
- **Cross-sectional design.** Causal inference requires experiments, such as randomising notification frequency or type, or panel data tracking the same users over time.
- **Sampling.** A non-probability sample limits generalisability; stratified sampling across regions, wallet platforms and income levels would improve representativeness.
- **Unmeasured variables.** Financial literacy, self-control, merchant category and wallet platform were not modelled. Future studies could use logistic regression for the impulse outcome, mediation analysis (engagement as mediator) and interaction terms (notification type × income).

8. Conclusion

This study examined how digital wallet notifications relate to spending behaviour using chi-square, ANOVA and multiple regression. Higher notification frequency was associated with markedly more impulse purchasing, spending differed significantly by notification type with reward-based messages linked to the highest spending, and daily notification volume remained a significant predictor of monthly spending after controlling for age, income and engagement. Notifications appear to work as behavioural nudges whose force depends on both how often they arrive and what they offer. Because the present dataset is simulated, these conclusions illustrate the analytical approach rather than establishing empirical facts; replicating the analysis with real respondent data, using the accompanying workbook, is the natural next step.

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Appendix A. Survey Questionnaire

Section 1 – Demographics. Q1 Age (years). Q2 Gender (Male / Female / Other). Q3 Monthly income (₹ '000).

Section 2 – Wallet use and notifications. Q4 On average, how many digital-wallet notifications do you receive per day? (number). Q5 Which type of notification do you receive most often? (Cashback/Offer; Transaction Alert; Payment Reminder; Promotional). Q6 Approximately how much did you spend through digital wallets last month (₹)?

Section 3 – Engagement (1 = Strongly disagree … 5 = Strongly agree). E1 I read most wallet notifications when they arrive. E2 I often open the wallet app after receiving a notification. E3 Notifications make me aware of offers I would otherwise miss. E4 I have completed a transaction directly because of a notification. (Engagement score = mean of E1–E4.)

Section 4 – Impulse purchase. Q7 In the last month, have you made a purchase you had not planned after seeing a wallet notification? (Yes / No).

Appendix B. Reproducing the Analysis in Excel

- Paste responses into the 'Data' sheet of Digital_Wallet_Notifications_Analysis.xlsx (columns A, B, E, F, H–L); category columns C, D and G are formulas.
- Chi-square: 'ChiSquare' sheet (COUNTIFS, CHIDIST, CHITEST). ANOVA: 'ANOVA' sheet (AVERAGEIF, SUMPRODUCT, FDIST). Regression: 'Regression' sheet (LINEST, TDIST, TINV, CORREL).
- Equivalent menu route: Data → Data Analysis → 'Anova: Single Factor' and 'Regression' (Analysis ToolPak add-in). The workbook formulas give the same results and update automatically.