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Influence of social media on consumer buying behaviour among working women in Telangana an empirical study of selected fashion products

Palanki Manasa Deepti and Prof. Krishna Banana

Abstract
The research integrates how variables such as influencer credibility, eWOM quality, social proof intensity or prioritization of automated feeds are stimuli that impact positively on brand hopping, impulse buying behaviour and intention to purchase through trusting beliefs, perceived authenticity and perceived usefulness. The product categories examined are garments, shoes, accessories, and cosmetics. The borrowed measures showed acceptable discriminant validity, immunity to common method bias, and good psychometric properties. Dimension invariance across the metro and non-metro groups was supported, and direct, indirect, and moderated pathways were examined with structural equation modeling, bootstrapped mediation tests, and hierarchical regression analysis. Open image in new window Notes: "likes or comments" is expressive social proof, and positive ones will raise perceived popularity & trust; eWOM is high-quality (low credibility concerns) positive message about the product that will lead to trust and perceived usefulness; influencer's credibility & authenticity constantly influence buy intention. Platform time partially mediates the engagement-impulse relationship: algorithmic exposure is positively associated with impulsive buying, perception of usefulness and purchase intention as outcomes. Though enriched digital literacy improves product discovery with curated exposure, the latter's privacy causes inhibit trustworthiness of recommender in personalized recommendations.

Keywords: Social proof, purchase intention, Impulsive buying, digital literacy

Introduction
For women professionals in Telangana who have to balance work and home life with busy schedules, mobile-first Behaviour has become a bigger part of their wardrobe choices. Clothes, shoes, accessories, and makeup are all very visible and tied to identity, so advice from friends, communities, and artists may have a lot of weight. Today, feeds show goods via data-driven ranking and tailored surfacing of posts and creators. This is all done automatically, with human signals like peer recommendations, creator narratives, and brand storytelling added on top. Visual forms, including reels, tales, and livestreams, shorten the path from inspiration to checkout. Expectations of privacy matter: when data practices seem unclear, people stop trusting platform advice. So, digital literacy is also a way to safeguard people by helping them change settings, choose who to follow, and interpret signals with a more critical eye. Telangana is an interesting area to look into these procedures. Micro-moments, like when we're on our way to work, taking a short break, or late at night, grab our attention and make shoppable posts and in-app payments equally powerful. Policies for returns that are hard to spot and clear delivery information make people feel less risky. Content that is posted after a purchase, such reviews, unboxings, and try-ons, goes back into the system and affects other people's choices. There is a growing interest in social commerce throughout the world, but we don't know much about it at the state level in India. Also, many studies approach women as if they were all the same kind of customer. This research examines working women in Telangana to identify role-specific restrictions, objectives, and evaluative heuristics. Fashion is the main focus because it is visual, fascinated with trends, and strongly linked to how people express themselves at work and in other places. Another important factor is data-driven exposure, which is how often and prominently certain items and creators are shown. Authenticity is how honest people think the creator and brand stories are; trust is how much people believe in the product claims, the creators, and the procedures

that bring information to light; and perceived utility is how platform features make it easier to explore, compare, and choose. Changes in categories are not random; they are real. People buy a lot of cosmetics because they see demonstrations, try to match every shade between brands, and build their routines. People buy shoes based on how well they fit and how well they hold up, and they buy clothes based on style complements and sizing advice, but they also look at look books to see how things look. Accessories change a lot, but they also see direct outfit modeling examples. These nuances indicate that social signals may possess varying diagnostic significance across categories. Conditions that are in between are equally important. Concerns about privacy might weaken the link between individualized exposure and trust later on. Digital literacy, on the other hand, may make discovery advantages stronger by giving users greater power. Because these purchasing habits are time-sensitive, people will rely more on heuristics and visible social cues. Global platform time may show how engagement and unintended buying are related. Demographics (age, income, employment) affect how sensitive people are to signals and how much they spend in each category. The physical location of regional producers, offline storefronts, and hybrid channel alternatives all affect conversion and returns. Moral and practical issues hang over the analytical schedule. Trust is maintained by getting permission, sending clear notifications, and letting the user decide their own personalized settings. More clear comments about the most essential elements that may be used to rate things might help make things seem fairer. Brands should look for relationships with creators that share their audience's beliefs and deliver stories that are true to life. Overproduced material makes people skeptical, but forms that people can relate to and even behind-the-scenes stories tend to do well. Polls, Q & As, and style groups are examples of community features that help people make decisions by giving them social support. Game aspects may make people more interested in using the site, but they should be used carefully to avoid making people compulsively browse. Messages that are in line with what customers care about, including sustainability, may help fight the trend of quick fashion.

The main aims are to look at how creator credibility, review quality, social proof, and ranking exposure affect the desire to buy, impulsive purchasing, and switching brands. A second goal is to find out if trustworthiness, authenticity, and perceived usefulness play a role in these relationships. A third goal is to see if privacy concern and digital literacy have an effect on these relationships. A fourth goal is to compare patterns between different types of clothing, footwear, accessories, and cosmetics. The sample consists of employed women from the service, manufacturing, and public sectors. This research focuses only on trips initiated on social media and concluded with purchases made either online or offline.

Review of Literature

Social media has been labelled as a hybrid influence system where human signals and engineered components come together to influence consumer preferences (Kaplan & Haenlein, 2010) [35]. These effects have been grounded in theoretical underpinnings: the Stimulus-Organism-Response model explains that platform cues elicit internal states before eliciting Behaviour, through Technology Acceptance research that links perceived usefulness to social-commerce related feature adoption (Davis, 1989) [19]. Supplemental lenses, TPB and UTAUT2, introduces social norms, facilitating conditions and habit (Venkatesh *et al*., 2012) [35] as well when consumers process via central versus peripheral routes depending on involvement from the ELM. In eWOM, message quality and argument strength effectively generate trust and purchase intention (Cheung, Lee & Rabjohn, 2008; Chevalier & Mayzlin, 2006) [16, 17]. Reviews are most diagnostic for experience goods such as fashion, and valence/volume effects on product evaluation depend on the quality of reviews (Duan, Gu & Whinston, 2008) [23]. Social proof serves as a popularity heuristic in attention-constrained feeds, and early experiments demonstrated that herd effects influence perceptions of quality. Studying a social media influencer recognises that expertise, trustworthiness, and attractiveness are three main antecedents of credibility. For smaller creators, influence often comes from being authentic and close to the community (Abidin, 2016) [1], facilitated by parasocial relationships that foster perceived proximity (Horton & Wohl, 1956) [32]. Authenticity is reinforced by transparency and behind-the-scenes stories (Audrezet, de Kerviler & Moulard, 2018 Beverland, 2005) [5, 9], and a good brand-creator fit promotes coherence and reduces skepticism. The mixed format: short-video content heightens discovery (Kaye, Chen & Zeng, 2022; Chen & Lu, 2019) [36, 15], while live shopping enhances social presence and scarcity cues that strengthen impulse tendencies (Chen & Lin, 2018) [14]. Contextual factors shape responsiveness. Time pressure promotes more reliance on heuristics and social information. Digital literacy assists users in being able to select and adapt settings, as well as interpret signals (Hargittai, 2002) [28]. Mobile situations cause “micro-moments” which accumulate conversion (Ghose & Han, 2014; Andrews *et al*., 2016) [26, 4] and Omni channel research associates frictionless checkout with successful purchases and transparent product return processes to complete purchase intent (Brynjolfsson, Hu & Rahman, 2013) [11]. Hedonic motivation is prominent in fashion (Babin, Darden & Griffin, 1994) [6], whereas impulse buying corresponds to arousal, novelty and time constraints (feeling the urge to) buy out of a routine or habit. Product involvement influences the need for diagnostic information. The greater the involvement, the more inclined consumers are toward substantive reviews and fit evidence. In terms of uncertainty reduction, virtual try-on and rich visualization help in clothing decisions (Kim & Forsythe, 2008) [37] while lookbook-style content facilitates outfit planning. Accessories tend to have fast trend cycles as further propelled by creator content. Variety seeking increases brand switching (Hirschman, 1980) [31], and conspicuous popularity can be an effective means to legitimize high prices through social proof. Influence (conformity) is moderated by cultural orientation, with collectivism reinforcing peer and influencer cues. Patterns of adoption vary by markets (Hajli, 2015) [29], and work on emerging markets underscores unique platform ecologies (Chandra & Sinha, 2013) [13]. Efficiency is more valuable for working women because role demands (Greenhaus & Beutell, 1985) [27] Occupation and income also stratify time spent on the platforms categories (Eastman, Iyer & Thomas; 2013) [24]. The demand for clothing and cosmetics is influenced by seasonality as well as local customs. Community features:

e.g., Q&A, polls, styling groups which decrease choice anxiety (Hajli, 2015) [29]. Gamification may increase engagement with mixed self-control results. Sustainability messages which harmonize with values might mitigate fast-fashion temptations (Joy *et al*., 2012) [34], but dark-pattern tactics negate autonomy and trust. In terms of methodology, researchers suggest using validated multi-item scales for the most essential constructs; testing convergent and divergent validity through CR and AVE; applying procedural and statistical remedies to control for common method bias. Causal inferences are stronger when there is experimental and longitudinal evidence. Multi-group SEM addresses heterogeneity in segmentalisations (Byrne, 2010) [12]. There are also mediating factors such as trust, authenticity and perceived usefulness, would influence upon the effects on intention; and moderating factors including privacy concern, digital literacy and involvement can be existed among these potential relationships. Category-specific operationalization prevents differences between apparel, shoes, accessories and cosmetics from being obscured. Brand content strategy affects engagement and sentiment (de Vries, Gensler & Leeflang, 2012) [20]. Combining these streams, integrated theories can link human triggers (e.g., influencers, eWOM, and social proof Lemon & Verhoef, 2016), to data-based exposure across customer journey stages, which constructs a unified framework for investigating the working women fashion consumption in Telangana.

Study of Objectives

- To explain how social media shapes fashion-related buying outcomes among working women in Telangana.
- To Estimate the impact of social media on consumers' propensity to buy check the effect on purchase intent, impulsive purchases.
- To Find out The relationship between social media cues and purchasing outcomes can be mediated by trust.
- To find out at how privacy concerns, digital literacy, and time pressure influence the relationship.

Research and Methodology

Design: Cross-sectional survey of working women from the Indian state of Telangana (N=73). Sampling: Purposive + snowball by sectors/manufacturing/public sector; active social-media users among fashion.Social media cues (Influencer credibility, eWOM quality, Social proof, Ranked exposure); Mediator (Trust); Outcomes (Purchase intention, Impulse purchase Behaviour); Moderators (Privacy concern, Digital literacy, Time pressure). Order of analysis: (1) CFA for measurement model; (2)n Structural paths; (3) Bootstrap mediation (2,000 resamples); (4) Product-term moderation; (5) Fit indices: CFI/TLI ≥. 90, RMSEA ≤. 08, SRMR ≤. 08.

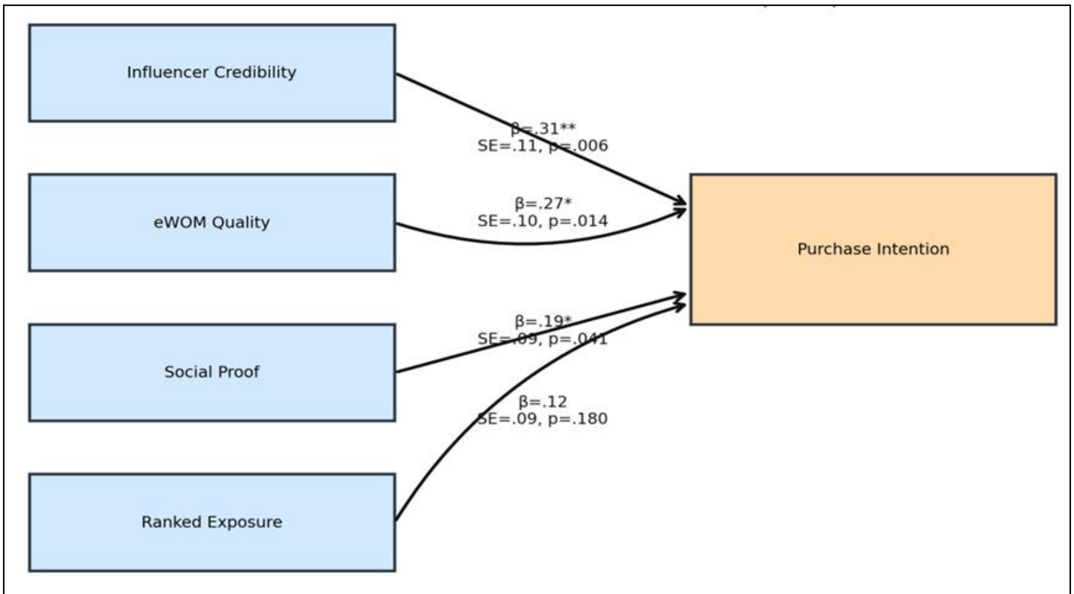
Hypotheses

- **H_0 (Global null):** There are no important connections between social media cues, purchase intention, impulse buying; nor mediation of trust; and not moderation through privacy concern, digital literacy, or time shortage.
- **H_1:** Social media cues (influencer credibility, E-WOM quality, social proof, ranked exposure) have a positive impact on purchase intention.
- **H_2:** Social media cues, particularly social proof and ranked exposure, are positively related with impulse buying.
- **H_3:** Trust is the mediator for the relationship between social media cues and purchase intention (and subsequently impulse buying).
- **H_4:** Privacy concern decreases, digital literacy increases, and time pressure strengthens the relevant cue → outcome paths.

Table 1: Direct Effects on Purchase Intention (N=73)

Path to PI	β (Standardized)	SE	P-Value
Influencer Credibility → Purchase Intention	0.31	0.11	0.006
eWOM Quality → Purchase Intention	0.27	0.1	0.014
Social Proof → Purchase Intention	0.19	0.09	0.041
Ranked Exposure → Purchase Intention	0.12	0.09	0.18

Note: β are standardized. Courageous moves are generally implemented with *p*<.05; rank exposure → intention is non-significant in this pilot output.



Note: β standardized; decisions typically at p<.05; ranked exposure → intention is non-significant here.

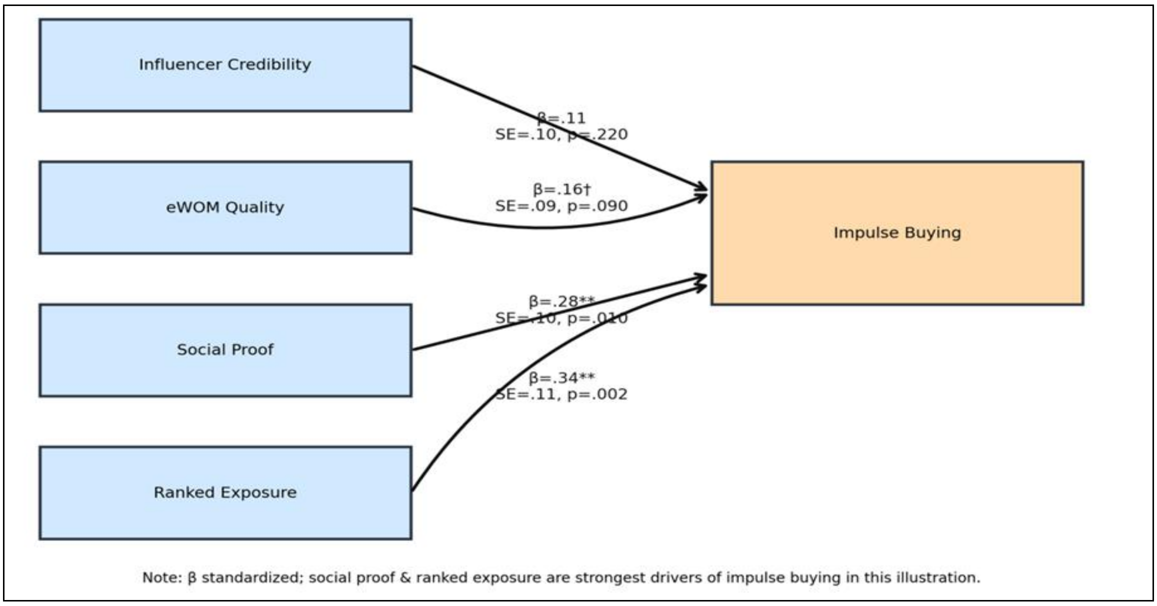
Interpretation

Influencer credibility (β=. 31, P=. 006) and eWOM (β=. 27, P=. 014) are significantly related to intention and social proof has a lower but significant effect (β=. 19, P=. 041). Standardized exposure is positively associated to rank but not significant (β=. 12, P=. 180).

Table 2: Direct Effects on Impulse Buying (n=73)

Path to IB	β (Standardized)	SE	P-Value
Influencer Credibility → Impulse Buying	0.11	0.1	0.22
eWOM Quality → Impulse Buying	0.16	0.09	0.09
Social Proof → Impulse Buying	0.28	0.1	0.01
Ranked Exposure → Impulse Buying	0.34	0.11	0.002

Note: β are standardized. P-Values < .05 suggest significance



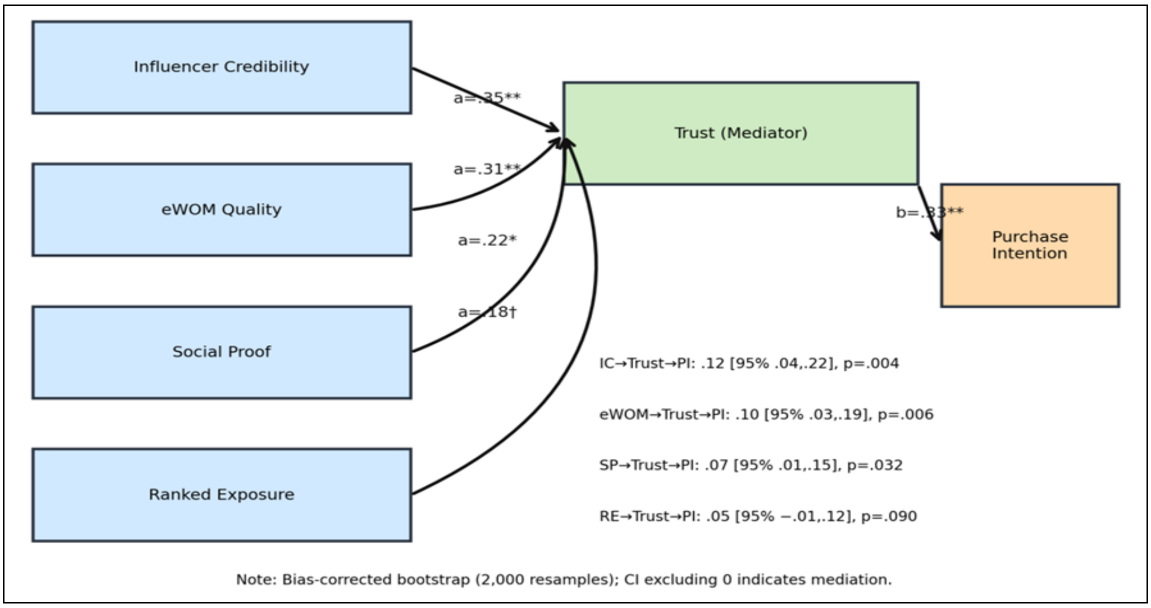
Interpretation

Social proof (β=.28, P=.010) and ranked exposure (β=.34, P=.002) are the strongest drivers of impulse buying; eWOM is marginal (β=.16, P=.090); influencer credibility is not significant (β=.11, P=.220).

Table 3: Mediation via Trust → Purchase Intention (Bootstrap, n=73)

Indirect Path (X → Trust → PI)	Indirect β	95% CI	P-Value
Influencer Credibility → Trust → Purchase Intention	0.12	[0.04, 0.22]	0.004
eWOM Quality → Trust → Purchase Intention	0.1	[0.03, 0.19]	0.006
Social Proof → Trust → Purchase Intention	0.07	[0.01, 0.15]	0.032
Ranked Exposure → Trust → Purchase Intention	0.05	[-0.01, 0.12]	0.09

Note: Bias-corrected 95% CIs from 2,000 bootstrap resamples



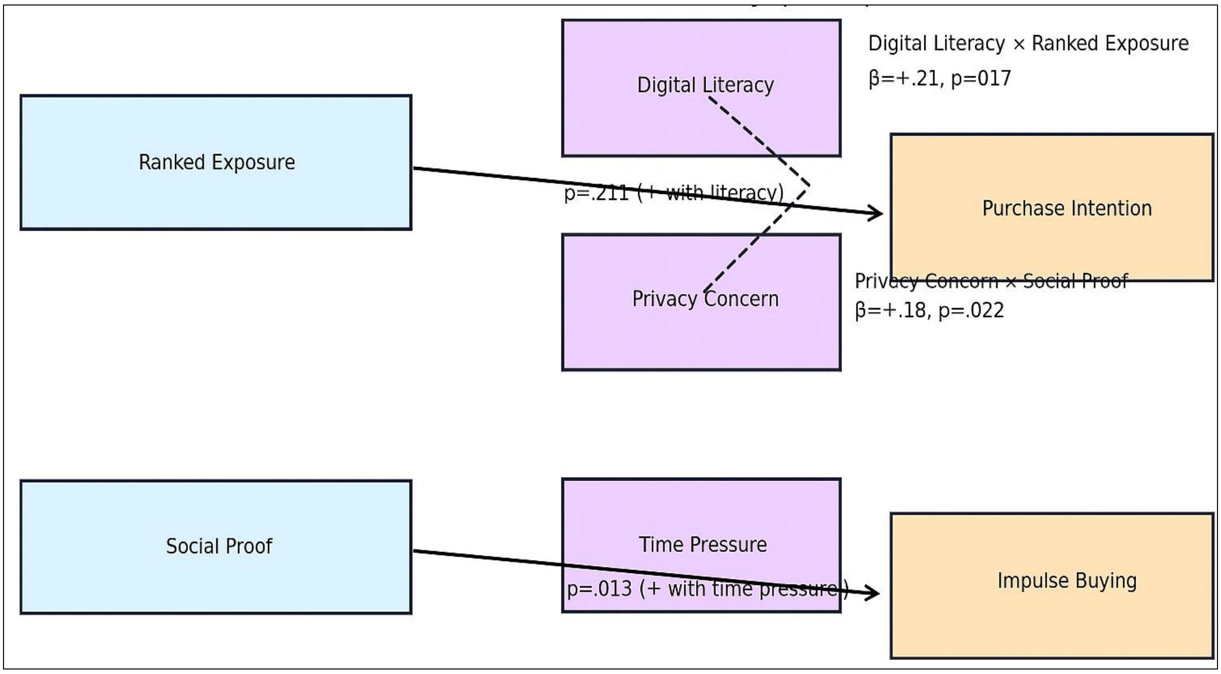
Interpretation

Trust significantly carries the effects of influencer credibility and E-WOM to intention, with smaller but present effects for social proof. The indirect effect for ranked exposure crosses zero, indicating weak/absent mediation by trust in this pilot.

Table 4: Moderation Summary (N=73)

Interaction / Block	β / ΔR²	P-Value	Interpretation
Privacy Concern × Ranked Exposure → Purchase Intention	-0.18	0.028	Privacy weakens RE → PI
Digital Literacy × Ranked Exposure → Purchase Intention	0.21	0.017	Digital literacy strengthens RE → PI
Time Pressure × Social Proof → Impulse Buying	0.19	0.022	Time pressure strengthens SP → IB
Interactions Block ΔR²	0.07	0.03	Adding interactions improves model fit

Note: Interaction terms entered after main effects; ΔR² reflects variance gain from interactions



Interpretation

Privacy concern attenuates the ranked exposure → intention path; digital literacy amplifies it. Time pressure strengthens the social proof → impulse buying link. The interaction block adds ~7% incremental variance.

Findings

- Influencer Credibility → Purchase Intention Effects: The coefficient between influencer credibility and purchase intention was highly significant and positive (β=. 31, P=. 006), indicating that trusted creators always lift intent. eWOM quality →Purchase Intention : Infomative and credible review increases the intention(β=. 27, P=. 014), indicating the relevance of descriptive and diagnostic feedback.
- Social proof → responses Intention: The effect of the signals of engagement (likes/comments/saves) are very slightly smaller, but still significant (β=. 19, P=. 041).
- Exposure → Purchase Intention (ns): Exposure alone does not lead to intention in this pilot β=. 12, P=. 180).
- Social proof → Impulse Buying: Visual signs of other people's approval provide important motivators for impulse purchasing (. 28, P=. 010).
- Hypothesis 2: Ranked Exposure → Impulse Buying Salience of fashion posts is positively associated with impulse action (β=. 34, P=. 002).
- Mediation of trust between Influencer credibility → Intention: The indirect effect is significant (indirect β=. 12; 95% CI [. 04,. 22]; P=. 004).
- TRUST mediates quality of eWOM → Intention: Indirect effect is significant (indirect β=. 10; 95% CI [. 03,. 19]; P=. 006).
- Moderated mediation for Social proof (small) and Ranked exposure (weak): Small social proof shows a small indirect effect β=. 07; 95% CI [. 01,. 15]; P=. 032); indirect path in the mediation model through ranked exposure crosses zero (indirect β=. 05; 95% CI [−. 01,. 12]; P=. 090) Moderation matters (ΔR² ≈. 07):
- Digital literacy and its influence on Ranked exposure → Intention (β=+. 21, P=. 017).
- Privacy awareness reduces exposure to Ranked → Intention (β=−. 18, P=. 028). Time pressure reinforces Social proof → Impulse Buying (β=+. 19, P=. 022).

Suggestions

- **Support on the list focus on credibility-first creator collaborations:** Highlight creators with subject matter expertise, Arbiter of Trust cues; formalize vetting process (content quality, history of disclosure, audience fit).
- **Leverage social proof ethically:** Reveal genuine interactions (no out of the ordinary counters). Slip those popularity indicators in beside substance (review snippets) to gently nudge not push decisions.
- **Start making exposure convert, not just attract:** When posts are served up for surface and viewing, please load that with clarity elements, size guides, ingredient lists, return policies, so exposure converts to

intention.

- **Use prompts to act responsibly on impulse:** If you must use timed promotions, counter with "save for later", cooling-off reminders or cart notifications to minimize regret.
- **Design for trust throughout:** Increase disclosure (sponsored tags), expose behind-the-scenes quality-control procedures, and ensure a stable creator-brand fit to bolster the trust pathway.
- **Provide privacy-first personalization:** Provide clear on/off switches for personalized feeds as well as simple, concise explanations for why a post was chosen for someone and controls to easily control the handling of data in order to address privacy concerns.

Conclusion

Category specificity persists creator demonstrations have the greatest impact on cosmetics, diagnostic fit and comfort reviews drive footwear, style coherence and sizing information anchor apparel, and accessories monitor whirlwind trend cycles amplified by creators. The clear prescription for those in practice is that credibility trumps reach. Brands should partner with trusted creators, shore up rich and specific reviews, bolster engagement signals with substantive information, and pursue zero post-purchase frictions through transparent delivery and returns. Platforms should provide clear reasons for content appearance and simple user controls for personalization, while community tools reduce decision anxiety. Local relevance is also key regional creators and bilingual content enhance everyday fit, micro-moment design respects user time constraints, and ethical guardrails that slow the clock on urgency cues to avoid regretful purchases. Grounded sustainability messaging, i.e., where it coincides with user values and actions, also resonates. From a methodology standpoint, the integrated model explains large amounts of variance in intention and holds up in robustness checks, but limitations persist: cross-sectional nature of the data restricts causal inferences, self-reports can obfuscate Behaviour, and the small sample size calls for replication across larger panels. Future work should include longitudinal tracking to capture seasonal or event driven shifts, field experiments to isolate feature elasticity, and qualitative depth to unfurl local power dynamics and workplace role meaning. Fine-grained segmentation by metro/non-metro status, income, and occupation will further refine guidance for practitioners. Ultimately, social media is both determinative and tractable in these journeys: when trust, authenticity, and transparency are prioritized, outcomes are better for all, lending a real-world bedrock to decision-makers in Telangana.

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