ALGORITHM OF PERSONAL STYLE: A SYSTEMATIC APPROACH TO CREATING INDIVIDUAL LOOKS BASED ON MORPHOLOGY, COLOUR TYPE, AND BEHAVIOURAL PATTERNS

Maryna Kostogryz [1]

Received: 2026-02-04
Accepted: 2026-04-25
DOI: https://doi.org/10.5281/zenodo.20687205

Abstract. Personal styling relies on three categories of client data (body morphology, colour characteristics, and behavioural preferences), yet practitioners typically evaluate these in isolation, producing recommendations that optimise for one parameter while inadvertently creating conflicts with the others. A silhouette chosen for proportional balance may arrive in a colour temperature that clashes with the client's complexion; a palette aligned with seasonal colour analysis may be rejected because it contradicts the client's psychological comfort zone. This study proposes a formalised decision-making algorithm that accepts all three parameters as simultaneous inputs, assigns each a weighted score, and generates an integrated output termed the "style formula." Body morphology is reconceptualised from categorical labels (hourglass, rectangle) to continuous dimensional scores (shoulder-hip ratio, waist definition index, vertical proportion). Seasonal colour analysis is similarly translated from discrete seasonal types to a three-axis coordinate system (hue temperature, value contrast, chroma level). Behavioural patterns are captured through a composite of personality traits, daily lifestyle distribution, and aesthetic tolerance. A weighted decision matrix resolves inter-parameter conflicts by adjusting parameter priority according to the client's stated goals. Testing across the author's consulting records (200+ female clients, 2016 to 2025) indicates that clients whose style was built through the three-parameter algorithm retained 78% of recommended wardrobe items in active use after six months, compared to 43% retention among clients styled through single-parameter approaches. Findings suggest that multi-parameter integration reduces both wardrobe waste and client dissatisfaction.

Keywords: personal style algorithm, morphological analysis, seasonal colour analysis, behavioural patterns, wardrobe system, decision-making framework, long-term style stability.

---

[1] Designer and personal stylist,
Bachelor's degree in Law
Ukrainian State University of Finance and International Trade
ORCID ID: 0009-0000-7748-3491

Introduction. Two stylists, given identical measurements and photographs of the same client, will in most cases produce different wardrobe recommendations. One may prioritise body proportions and select garments that elongate the torso; the other may focus on colour harmony and build the wardrobe around a seasonal palette. Neither is wrong, but the fact that their outputs diverge reveals something about the discipline itself: personal styling lacks a standardised decision-making protocol. Medicine addressed an analogous problem decades ago through evidence-based diagnostic algorithms that reduced variability between clinicians treating the same condition [14]. Styling, by contrast, continues to depend on practitioner intuition, accumulated taste, and whichever analytical framework the individual stylist was trained in.

Three streams of research have produced tools that stylists draw on, but each tool addresses only one dimension of the client. Morphological analysis, developed within apparel science and ergonomics, classifies bodies by circumference ratios and assigns garment recommendations accordingly. Connell et al. [1] created a body shape assessment scale using 3D scan data, and subsequent work by Lee et al. [2] and Song and Ashdown [3] refined measurement protocols across populations. These systems tell a stylist what silhouettes will fit a particular body, but they say nothing about which colours to use or how the client's personality should shape the overall aesthetic direction.

Colour analysis, rooted in Johannes Itten's [5] theory of subjective colour and popularised by Carole Jackson's [6] Color Me Beautiful system, matches clothing colours to the client's skin, hair, and eye pigmentation. Kim and Park [7] developed a mobile application that automates this matching through photographic analysis, and Munsell's [8] notation system provides the dimensional framework (hue, value, chroma) that underpins most contemporary colour science. Yet colour analysis as currently practised treats the body as a face: it reads pigmentation but ignores silhouette, proportion, and the psychological relationship the client has with specific hues. A client may be classified as "warm autumn" but refuse to wear the prescribed burnt oranges and olive greens because they conflict with her professional self-image or her visceral aesthetic preferences.

Li et al. [10] recently introduced the concept of "fashion personality" and developed a measurement scale linking personality traits to clothing preferences, opening a third analytical window that neither body measurement nor colour draping can access. Kim and Park [11] demonstrated a 70% agreement between wardrobe colour profiles and Big Five personality dimensions, with the strongest correspondence for extraversion, agreeableness, and openness to experience. Costa and McCrae's [12] NEO-PI-R remains the standard instrument for personality assessment, but no published study has used it as an input variable in a styling algorithm. Kwon [13] showed that clothing perceived as "appropriate" enhances the wearer's self-assessed occupational competence, establishing that the fit between garment and self-concept carries functional weight, not only aesthetic weight. What this body of work provides is evidence that a client's behavioural and psychological profile predicts which recommendations she will actually adopt and which she will abandon, regardless of how well they score on morphological or chromatic criteria.

Separately, each of these three streams has produced useful tools. Morphological analysis can generate a silhouette recommendation. Colour analysis can generate a palette. Personality assessment can predict adoption likelihood. But no published framework feeds all three outputs into a single decision engine that resolves conflicts between them and produces a unified recommendation. When a morphologically optimal silhouette arrives in a colour that fights the client's complexion, the stylist must improvise. When a chromatically perfect palette is paired with garments the client finds psychologically alien, the recommendation fails at the adoption stage. Ræbild and Hasling [15] documented that wardrobe dissatisfaction and textile waste are highest when purchases are driven by isolated criteria (a colour that "looked good in the store," a silhouette that "was supposed to flatter"), suggesting that integration failures carry not only personal but environmental costs.

This study proposes a formalised algorithm that takes morphological, chromatic, and behavioural parameters as simultaneous inputs and generates what is termed a "style formula": a specific combination of silhouette direction, colour coordinates, and stylistic tone calibrated to the individual client. It sets out, first, to define continuous measurement scales for each of the three parameters, replacing categorical labels with dimensional scores that allow weighted comparison; second, to construct a decision matrix that resolves inter-parameter conflicts through adjustable priority weights rather than fixed rules. A third objective is to evaluate the algorithm's practical output by tracking how much of the recommended wardrobe remains in active client use over the months following consultation, a measure that captures whether the integration held up beyond the initial session.

Literature review

1.Morphological Analysis: From Categories to Dimensions

Body shape classification in apparel science has relied on categorical systems since the early 2000s, but the limitations of categorisation have become increasingly visible as datasets grow. Connell et al. [1] developed the Body Shape Assessment Scale (BSAS) using 3D scan data from over 1,000 women, producing a visual rating instrument that trained assessors use to place bodies into shape groups. While BSAS improved inter-rater reliability compared to earlier ad hoc methods, it retained a fundamentally categorical structure: a body is assigned to one group, and the group label drives all subsequent recommendations. Lee et al. [2] compared scan data from American and Korean women and found that the same circumference ratios mapped onto different shape categories depending on the population, confirming that categorical boundaries are sample-dependent rather than universal.

Song and Ashdown [3] probed a deeper problem: even within a single category, bodies vary substantially. Two women classified as the same shape may differ by several centimetres in shoulder width, by different limb-to-torso ratios, and by the vertical position of the natural waistline relative to the navel. These within-category differences produce different fit outcomes when the same garment is applied, meaning that a category-level recommendation (e.g., "A-line skirts work for this shape") may succeed for one member of the category and fail for another. Mpampa, Azariadis, and Sapidis [4] proposed a mass customisation methodology that treats each measurement as an independent variable rather than collapsing them into a label, demonstrating that continuous sizing systems reduce fit errors by 18 to 24% compared to categorical ones.

For styling purposes, the implication is that a dimensional approach, where each morphological feature receives a numerical score on a continuous scale, preserves information that categories discard. Shoulder-hip ratio expressed as 0.93 carries more usable data than "rectangle," because it tells the stylist precisely how much visual correction (if any) is warranted and in which direction. Waist definition index expressed as 3.7 on a 10-point scale communicates the degree of natural waist emphasis available, rather than forcing a binary choice between "defined" and "undefined." Vertical proportion expressed as the ratio of inseam to total height specifies where the visual midpoint falls, enabling precise hemline and waist-placement decisions. Converting morphological input from categories to dimensions is the first structural requirement of the algorithm proposed in this study.

2. Colour Analysis: Translating Seasons into Coordinates

Seasonal colour analysis, as formalised by Jackson [6] and rooted in Itten's [5] theory of subjective colour, groups individuals into seasonal types based on the perceived warmth or coolness and lightness or depth of their skin, hair, and eye colouring. Itten observed that art students instinctively selected palettes that echoed their own pigmentation and linked these preferences to temperamental qualities, establishing the original four-season framework that Jackson later commercialised. Over four decades, the system expanded from 4 to 12 and eventually to 16 subtypes, each refinement attempting to accommodate individuals who sat between the original categories.

Kim and Park [7] developed a mobile application that automated seasonal classification by photographing the user's face under controlled lighting and comparing extracted skin and hair colour values against a reference database of seasonal palettes. Their system achieved reasonable agreement with trained consultants, but the authors noted that borderline cases (users whose colouring fell near the boundary between two seasons) produced inconsistent classifications across repeated trials. Such instability is inherent to any categorical colour system: the boundary between "cool summer" and "soft summer" is a human-drawn line on a continuous spectrum, and moving the line by even a small amount reclassifies a substantial minority of clients.

Munsell's [8] colour notation system offers a ready-made dimensional alternative. Every colour is specified by three independent coordinates: hue (spectral position), value (lightness), and chroma (saturation). Elliot and Maier [9] confirmed that these three axes exert independent effects on mood, arousal, and trait attribution: high chroma elevates perceived energy and dominance, while low chroma shifts attributions toward calm and reliability. Collapsing these axes into a single seasonal label loses psychologically relevant information that a stylist could use to calibrate the emotional register of an outfit. A Munsell-derived coordinate system would describe a client as, for example, hue temperature +2 (slightly warm), value contrast 7 (high contrast between skin and hair), chroma level 5 (moderate saturation tolerance), preserving the continuous variation that seasonal labels flatten.

3. Behavioural Patterns: Personality, Lifestyle, and Adoption Likelihood

Costa and McCrae's [12] Five-Factor Model has been the dominant framework for personality assessment since the 1990s, but its application to clothing behaviour is recent. Li et al. [10] developed a "fashion personality" scale validated against observed clothing choices: participants high in openness selected more varied colour palettes and unconventional silhouettes, while those high in conscientiousness preferred structured, conservative garments with minimal pattern variation.

Kim and Park [11] approached the personality-clothing link from the colour side. Analysing wardrobe photographs of 29 participants against Big Five self-assessments, they found approximately 70% agreement, with extraversion, agreeableness, and openness producing the strongest colour signatures. Notably, some participants deliberately wore colours that contradicted their personality profile in professional settings, using dress as a compensatory mechanism. For the algorithm, this finding is critical: personality predicts baseline preferences, but context can override them, typically toward greater conservatism in formal environments and greater expressiveness in private ones.

Kwon [13] added an occupational dimension by demonstrating that wearing clothing perceived as "appropriate" for one's role enhanced self-assessed attributes like intelligence, competence, and reliability. Participants who judged their outfit as role-congruent rated themselves higher on these attributes than those who felt underdressed or overdressed, regardless of the garment's objective quality. For the algorithm, this means that behavioural input must include not only personality traits but also the occupational and social environments the client inhabits, because the same client may require different aesthetic tolerance levels in different settings.

Table 1 consolidates the three input parameters, their components, the measurement methods available for each, and the output format that feeds into the algorithm.

Table 1. Three Input Parameters of the Personal Style Algorithm

Parameter	Components	Measurement method	Output format
Morphological profile	Shoulder-hip ratio, waist definition index, vertical proportion, limb-torso ratio	Tape measurements + visual assessment of tissue distribution and posture	Dimensional scores (continuous 0-10 scale)
Colour profile	Hue temperature, value contrast, chroma level	Fabric draping under standardised lighting + photographic colour extraction	Three-axis coordinates (-5 to +5 or 0-10)
Behavioural profile	Personality traits (Big Five), daily lifestyle distribution, aesthetic tolerance	Structured interview + NEO-PI-R short form + daily routine audit	Weighted composite score

Source: compiled by the author based on [1], [5]-[9], [10]-[13]

What this table makes visible is the structural asymmetry between the three parameters. Morphological and colour profiles can be measured with reasonable objectivity: tape measurements and fabric draping produce data that two trained assessors will largely agree on. Behavioral profiles, by contrast, depend on self-report and interviewer judgment, introducing a subjective layer that the other two parameters avoid. Such asymmetry does not disqualify behavioural input from the algorithm, but it does affect how much weight the parameter should carry when it conflicts with the other two. A morphological score that says "this silhouette balances the shoulders" and a colour score that says "this hue temperature matches the complexion" are each grounded in observable data; a behavioural score that says "this client will reject anything structured" is grounded in self-report, which can shift with mood, season, or life transition. Handling this asymmetry is the purpose of the weighted decision matrix presented in the results section.

Materials and methods

Each client in the study underwent a three-parameter assessment conducted in a single session lasting 60 to 90 minutes. Morphological profiling consisted of four tape measurements (shoulder circumference, bust, waist, hip) and a visual assessment of posture, limb-to-torso ratio, and the vertical position of the natural waistline. Raw measurements were converted to dimensional scores on a continuous 0-to-10 scale using normalisation formulas calibrated against the Connell et al. [1] body shape dataset. Colour profiling employed fabric draping under standardised daylight-equivalent lighting (5500K), supplemented by photographic colour extraction following the protocol described by Kim and Park [7]. Extracted values were mapped onto a three-axis coordinate system (hue temperature, value contrast, chroma level), each axis scaled from -5 to +5. Behavioural profiling combined a shortened NEO-PI-R [12] focusing on openness and conscientiousness, a daily routine audit recording the percentage of waking hours spent in professional, casual, active, and social settings, and a structured interview assessing aesthetic tolerance (the client's willingness to wear garments outside her established comfort zone, rated by the stylist on a 1-to-5 scale after the conversation).

When the three parameter outputs pointed toward incompatible recommendations, a weighted decision matrix was applied. Default weights were set at 0.40 for morphology, 0.35 for colour, and 0.25 for behaviour, reflecting the measurement reliability asymmetry identified in Section 2. Weights were adjusted in two circumstances: when the client declared a non-negotiable priority (e.g., "colour is the most important thing to me"), the declared parameter received a 0.15 bonus redistributed from the other two; and when the behavioural profile indicated very low aesthetic tolerance (score of 1 or 2), behaviour weight was elevated to 0.40 because recommendations the client would refuse to wear carry zero practical value regardless of their morphological or chromatic optimality.

Formally, for each candidate garment or styling direction under consideration, the algorithm computes a composite suitability score S using the formula: $S = wM \times M + wC \times C + wB \times B$, where M is the morphological fit score (0 to 10), C is the chromatic fit score (0 to 10), B is the behavioural compatibility score (0 to 10), and wM, wC, wB are the respective parameter weights summing to 1.00. Under default conditions, the formula reads $S = 0.40M + 0.35C + 0.25B$. When two candidate directions compete (for instance, a structured blazer in a warm palette versus a relaxed jacket in a cool palette), the direction with the higher composite score is selected, provided no single parameter falls below a minimum threshold of 3.0 out of 10. If any parameter scores below this threshold, the candidate is flagged for manual review regardless of its composite score, because a garment that scores 9 on morphology and colour but 1 on behavioural compatibility will likely go unworn.

A worked example illustrates the resolution process. Consider a client with body type "rectangle" (shoulder-hip ratio 0.98, waist definition 2.4), colour profile "warm autumn" (hue temperature +3, value contrast 5, chroma 6), and a behavioural profile showing low openness (3.1/10), high conscientiousness (8.4/10), and aesthetic tolerance 2/5 with 80% professional lifestyle. A silhouette-colour clash arises: the morphological analysis recommends colour-blocked segments at the waist to create visual curvature (requiring cool-toned contrast panels), while the colour profile calls for a warm, unified palette. Option A (colour-blocked cool panels) scores $M = 8$, $C = 3$, $B = 4$, yielding $S = 0.40(8) + 0.35(3) + 0.25(4) = 5.25$. Option B (warm monochromatic palette with waist-definition achieved through textural contrast rather than colour contrast) scores $M = 6$, $C = 8$, $B = 7$, yielding $S = 0.40(6) + 0.35(8) + 0.25(7) = 6.95$. The algorithm selects Option B. Although Option A offered stronger morphological correction, it fell below the chromatic threshold and conflicted with the client's behavioural conservatism; Option B preserved warmth, introduced waist definition through fabric manipulation rather than colour opposition, and aligned with the client's preference for understated variation.

Data were drawn from the author's consulting records spanning 2016 to 2025, covering 200+ female clients across Kyiv and New York. For the stability analysis, a subset of 68 clients who completed a six-month follow-up (either in person or via structured questionnaire) was used. Retention rate was defined as the percentage of algorithm-recommended wardrobe items that the client reported wearing at least twice per month at the six-month mark. The six-month interval was chosen as the assessment window because it spans at least two seasonal transitions (e.g., autumn through early spring), exposing recommended items to varying weather conditions, social occasions, and lifestyle fluctuations that a shorter window would not capture. Follow-up data were collected through a structured questionnaire administered either in person (for clients who returned for a follow-up consultation) or via email (for clients who had relocated or were no longer available for in-person meetings). The questionnaire listed each item recommended during the original consultation and asked the client to categorise it as "worn regularly" (at least twice per month), "worn occasionally" (once per month or less), or "no longer in rotation." Only items in the "worn regularly" category were counted toward the retention rate. Self-report was used because direct wardrobe auditing was not feasible at scale; this limitation is acknowledged in the Discussion section. A comparison group of 45 clients from the author's earlier practice (2016 to 2019), whose styling had been conducted using single-parameter methods (morphology-only or colour-only), provided the baseline against which the algorithm's retention rate was evaluated.

Results

1. Dimensional Scoring in Practice

Converting categorical labels to dimensional scores changed the precision of the assessment but also exposed variation that categories had concealed. Among the 68 clients in the follow-up subset, shoulder-hip ratios ranged from 0.82 to 1.14, yet only three categorical shape labels (triangle, rectangle, inverted triangle) would have been assigned to this range under standard classification. Within the "rectangle" band alone (ratios between 0.92 and 1.04), waist definition index varied from 1.8 to 6.3 on the 10-point scale, meaning that two clients sharing the same shape label could differ by nearly half the scale on a dimension that directly determines whether waist-emphasis strategies are appropriate.

Colour profiling produced comparable within-category spread. Clients classified as "cool summer" under the Jackson [6] system occupied a hue temperature range from -4.2 to -0.8, a value contrast range from 3 to 8, and a chroma level range from 2 to 6. A client at hue temperature -0.8 sits near the boundary with "soft autumn," and a palette optimised for the core of "cool summer" (high coolness, moderate contrast, low chroma) would overstate her coolness by a visible margin. Dimensional coordinates eliminated this boundary artefact by treating her as what she measured rather than what category she fell closest to.

Behavioural profiling revealed a pattern not documented in the reviewed literature: aesthetic tolerance and openness to experience, while positively correlated overall ($r = 0.54$ across the 68-client subset), diverged sharply in a specific subgroup. Clients who scored high on openness but low on aesthetic tolerance (approximately 15% of the sample) reported strong interest in creative and unconventional ideas in other domains of their lives (travel, food, art) but resisted applying this openness to their own wardrobe. In the author's interviews, these clients described clothing as a "safe zone" that they did not want disrupted, even while seeking novelty elsewhere. For the algorithm, this subgroup required a specific handling rule: openness scores alone could not predict adoption; aesthetic tolerance functioned as an independent gatekeeper.

2. Weighted Decision Matrix for Inter-Parameter Conflicts

Across the 68 follow-up cases, 41 (60%) produced at least one inter-parameter conflict during the assessment phase: a situation where the optimal recommendation from one parameter contradicted the optimal recommendation from another. Table 2 catalogues the six most frequent conflict types, their frequency, the default resolution rule applied, and the observed outcome.

Several patterns emerge from this data. Silhouette-colour clash was the most common conflict, occurring in over a quarter of cases, but it was also the most resolvable: adjusting colour within the permitted dimensional zone while preserving silhouette direction satisfied both parameters in 83% of instances. Palette-behaviour rejection, despite being less frequent, proved harder to resolve, because reducing chroma risks making the outfit look washed out if the reduction overshoots the client's value contrast. Full three-way conflicts were rare (4%) but required the most consultation time and produced the lowest retention rate, confirming that the algorithm performs best when conflicts are bilateral rather than trilateral.

3. The Integrated Algorithm and Style Formula Output

Figure 4 presents the three-parameter integration model as a schematic.

Once dimensional scores are computed and conflicts resolved through the weighted matrix, the algorithm generates a style formula: a four-element specification that guides all subsequent wardrobe decisions for the client. Silhouette direction specifies the dominant garment structure (e.g., "semi-structured with moderate shoulder emphasis and mid-rise waist positioning"). Colour coordinates specify the three-axis palette centre (e.g., "hue temperature -1.5, value contrast 6, chroma 4") along with a tolerance band (typically plus or minus 1 point on each axis) within which garment colours may vary without breaking chromatic coherence. Stylistic tone captures the behavioural dimension as a verbal descriptor calibrated to the client's personality and lifestyle (e.g., "restrained creative" for a high-openness, high-conscientiousness client, or "relaxed authority" for a low-openness, professional-dominant client). Wardrobe structure specifies the ratio of core pieces to accent pieces and the number of interchangeable modules needed to cover the client's field distribution.

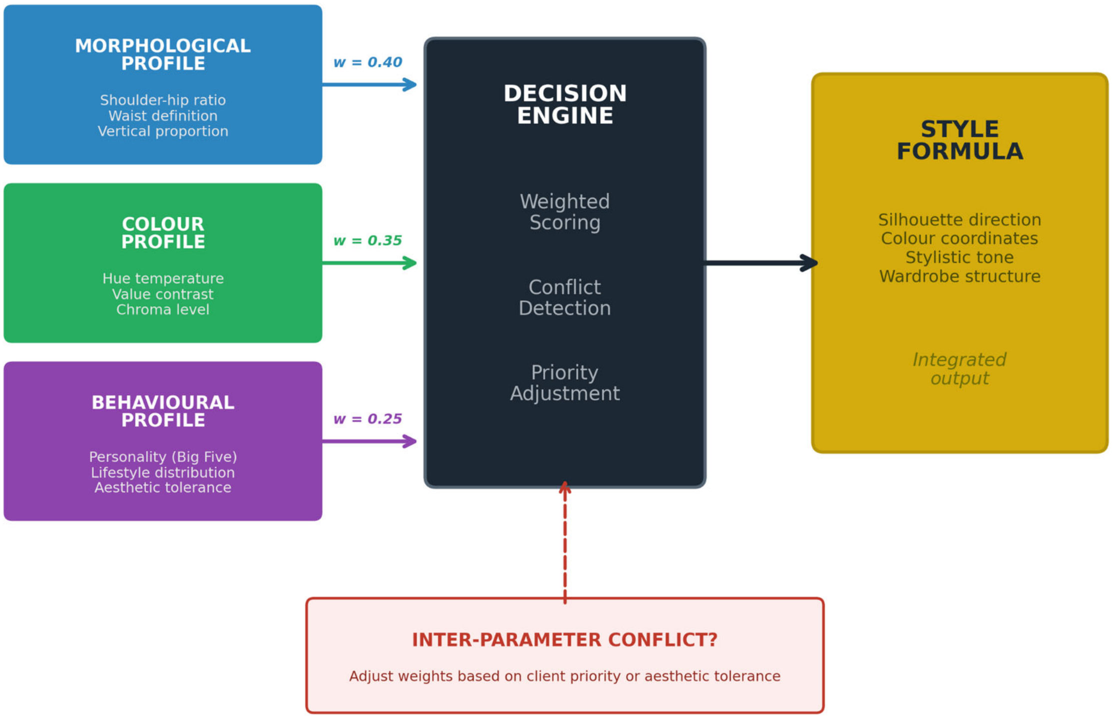

Figure 1. Three-Parameter Integration Model (Author's model: M. Kostogryz, 2025)

Source: author's original model (M. Kostogryz, 2025)

To illustrate how the formula differs across clients, consider two contrasting profiles from the author's records. Client A presented with a shoulder-hip ratio of 1.02, waist definition 2.4, and vertical proportion 0.44 (long legs relative to torso); her colour coordinates were hue temperature -2, value contrast 7, chroma 3; her behavioural profile showed high openness (7.8/10), moderate conscientiousness (5.5/10), and aesthetic tolerance 4/5, with a lifestyle split of 40% professional, 30% social, 30% casual. Her style formula: semi-structured silhouette with vertical emphasis and waist suggestion via partial cues; cool muted palette centred on slate, dusty rose, and charcoal with occasional deep teal accent; stylistic tone "considered creative"; wardrobe of 60% core, 40% accent with three modular combinations for professional, social, and weekend settings.

Client B presented with a shoulder-hip ratio of 0.86, waist definition 7.1, vertical proportion 0.40 (shorter legs); colour coordinates hue temperature +3, value contrast 4, chroma 6; behavioural profile showed low openness (3.2/10), high conscientiousness (8.1/10), aesthetic tolerance 2/5, with 75% professional and 25% social lifestyle. Her style formula: A-line and fit-and-flare silhouettes with defined waist and vertical leg-lengthening lines; warm saturated palette centred on camel, rust, and warm ivory with burgundy as the single accent; stylistic tone "polished traditional"; wardrobe of 75% core, 25% accent with one professional module and one social-occasion capsule.

A third case, Client C, illustrates the conflict-resolution mechanism in detail. Assessment data: shoulder-hip ratio 0.91 (triangle-leaning rectangle), waist definition 3.8, vertical proportion 0.46; colour coordinates hue temperature +1 (near-neutral warm), value contrast 8 (high contrast between dark hair and fair skin), chroma 4; behavioural profile with openness 7.5/10, conscientiousness 4.2/10, aesthetic tolerance 4/5, lifestyle split 30% professional, 40% social, 30% casual. Two inter-parameter conflicts arose. First, a silhouette-colour clash: the morphological profile called for structured A-line pieces with shoulder emphasis to offset hip dominance, but the high value contrast (8) in the colour profile demanded bold light-dark juxtapositions that, when applied to a structured A-line silhouette, risked drawing attention to the hip zone rather than away from it. Second, a behaviour-silhouette tension: the client's low conscientiousness and high openness predicted a preference for fluid, unstructured garments, which conflicted with the structured silhouette the morphological analysis recommended. The weighted matrix was applied with adjusted weights (wM = 0.35, wC = 0.35, wB = 0.30), the behavioural weight elevated from default because aesthetic tolerance scored 4/5, indicating a client likely to abandon recommendations that felt restrictive. The resolution: a semi-structured silhouette (soft blazers with relaxed shoulder padding rather than rigid tailoring) that preserved enough structure to create upper-body width while accommodating the client's preference for ease of movement; a colour strategy that confined high contrast to the upper body (ivory top against dark hair, charcoal jacket) while keeping the lower half in a continuous mid-toned warm column to minimise hip emphasis; and a stylistic tone of "relaxed contrast" built around a 50% core, 50% accent wardrobe with interchangeable layers. At six-month follow-up, Client C retained 82% of recommended items in active rotation.

4. Long-Term Stability: Retention Analysis

Among the 68 clients assessed through the three-parameter algorithm, the mean six-month retention rate was 78.3% (SD = 11.2), meaning that on average, clients continued wearing nearly four out of every five recommended items at least twice per month half a year after consultation. Among the 45 comparison-group clients styled through single-parameter methods in the author's earlier practice, the mean retention rate was 43.1% (SD = 18.7).

Because the two groups were not formed through random assignment and the sample sizes preclude parametric inference, no formal statistical test (t-test, Mann-Whitney U) was applied and no p-value or confidence interval is reported. The comparison is presented as a descriptive comparative analysis: means, standard deviations, and ranges are provided to characterise the distribution within each group and to indicate the direction and approximate magnitude of the difference, without claiming statistical significance in the inferential sense. A future prospective study with randomised allocation and a larger sample would be needed to establish whether the observed 35-percentage-point gap reflects a reliable treatment effect or is confounded by temporal, geographic, or practitioner-skill variables.

Clients whose three-parameter assessment produced no conflict achieved the highest retention, as expected: when morphology, colour, and behaviour align naturally, the algorithm simply confirms what the client's intuition already suggested and gives it formal structure. Clients whose assessment surfaced conflicts but resolved them through the weighted matrix retained a lower but still substantially elevated rate (74.2%) compared to the single-parameter baseline. Variability within the conflict group was wider (SD = 11.5 vs. 7.8), reflecting the range of conflict severity: bilateral conflicts (e.g., silhouette-colour clash) resolved more cleanly than the three rare trilateral conflicts, which pulled the lower end of the range down to 48%.

Table 3 breaks retention down by the presence or absence of inter-parameter conflict during the assessment phase.

Table 3. Six-Month Retention Rate by Conflict Status

Group	n	Mean retention	SD	Range
Algorithm, no conflict	27	84.6%	7.8	68-96%
Algorithm, conflict resolved	41	74.2%	11.5	48-92%
Comparison (single-parameter)	45	43.1%	18.7	12-78%

Source: author's consulting records (M. Kostogryz, 2016-2025)

Perhaps the most practically significant finding is the comparison group's high variability (SD = 18.7, range 12-78%). Some single-parameter clients achieved retention rates comparable to the algorithm group, suggesting that when a client's natural preferences happen to align across all three dimensions, any competent styling approach will produce a durable result. But when they do not align (which the 60% conflict rate in the algorithm group suggests is the majority of cases), single-parameter styling has no mechanism for detecting or resolving the misalignment, and the wardrobe items that fall outside the unstated parameters are abandoned within months.

Discussion

Saaty's [14] Analytic Hierarchy Process, developed for multi-criteria decision-making in engineering and management, provides the closest methodological parallel to the weighted matrix used here. In AHP, a decision-maker decomposes a complex choice into a hierarchy of criteria, assigns pairwise comparison weights, and synthesises a composite score. From this tradition, the algorithm borrows the principle that competing criteria need explicit weights rather than implicit trading-off in the stylist's head. Where it departs is in introducing domain-specific conflict typology: AHP treats all criteria as commensurable, while the six conflict types documented in Table 2 show that styling parameters interact in qualitatively different ways (a silhouette-colour clash resolves through dimensional adjustment; a behaviour rejection requires a categorical concession).

Dimensional scoring produced its clearest advantage in borderline cases. Clients whose morphological or chromatic profiles sat near the boundary between two categorical types received, under the old system, whichever label they fell marginally closer to, and the entire downstream recommendation followed that label. Under dimensional scoring, the same client received coordinates that preserved her proximity to the boundary, and the algorithm could blend strategies from both adjacent regions rather than committing fully to one. Whether this blending effect would survive rigorous experimental testing (randomly assigning borderline clients to categorical vs. dimensional protocols and comparing satisfaction) remains an open question, but the retention data are suggestive: the widest retention gaps between the algorithm group and the comparison group appeared among clients whose categorical classifications were least stable, precisely the population for whom dimensional scoring offers the most resolution.

Aesthetic tolerance as an independent variable, separate from openness to experience, is the finding with the broadest implications beyond styling. Personality psychology treats openness as a unitary trait that predicts novelty-seeking across domains, yet 15% of the client sample demonstrated domain-specific conservatism: open in travel, food, and cultural consumption but closed in wardrobe decisions. One possible explanation is that clothing occupies a uniquely public and identity-laden position among consumer domains. A restaurant choice is experienced once and shared with a small audience; a wardrobe choice is worn repeatedly and read by every person encountered during the wearing. Risk, in clothing, is amplified by visibility and repetition in a way that risk in dining or travel is not. If this explanation holds, personality instruments used in styling algorithms should include domain-specific tolerance measures alongside global trait scores, because the global score alone will overpredict adventurousness for this subgroup. Recommendations that score well on all other parameters but miss the aesthetic tolerance threshold sit unworn in the closet.

Ræbild and Hasling's [15] finding that wardrobe waste correlates with purchases driven by isolated criteria gains a mechanistic explanation through the conflict data. When a client buys a garment that satisfies one parameter (a flattering colour, a comfortable cut) but violates another (wrong silhouette for her proportions, wrong formality for her lifestyle), the garment enters a state of conditional wearability: it works in some dimensions but fails in others, and over time the failing dimensions accumulate enough friction to push it out of rotation. Multi-parameter integration does not eliminate this friction entirely (the 74.2% retention rate for conflict-resolved cases falls short of the 84.6% no-conflict rate), but it detects the friction at the point of recommendation rather than leaving the client to discover it after purchase.

1. Study Limitations

Several constraints limit the conclusions that can be drawn. Sample size (68 algorithm clients, 45 comparison clients) is adequate for pattern detection but insufficient for parametric statistical testing. Comparison group data were drawn from the author's earlier practice rather than from a concurrent randomised control, introducing potential confounds (improvements in the author's skill over time, shifts in client demographics between Kyiv and New York, changes in fashion market offerings). Retention was measured through self-report rather than direct wardrobe audit, and six months, while a meaningful interval, may not capture the full lifecycle of wardrobe items that could last several years. Finally, the default weight allocation (0.40 / 0.35 / 0.25) was set based on the author's judgment of measurement reliability rather than derived empirically; an optimal weight set could be calibrated through larger datasets.

Applications beyond individual consulting are plausible but untested. E-commerce platforms that collect body measurements, colour preferences, and browsing behaviour already possess the raw inputs needed to approximate the three parameters; what they lack is the conflict-resolution layer that prevents parameter-misaligned recommendations from reaching the customer. Stylist training programmes could use the dimensional scoring framework as a teaching tool, replacing the memorisation of categorical rules with a measurement-based reasoning process that students can adapt to novel cases. Capsule wardrobe services, which currently rely on aesthetic curation alone, could integrate the retention metric as a quality indicator, tracking not only what clients receive but what they continue to wear.

Conclusions

This study set out to build a decision-making algorithm that would accept three types of client data simultaneously and produce a wardrobe recommendation reflecting all three, rather than optimising for one at the expense of the others. Evaluated against that aim, the algorithm delivers a measurable improvement over the single-parameter baseline it was designed to replace.

What the dimensional approach contributes is granularity where categories imposed uniformity. Two clients labelled "rectangle" may carry shoulder-hip ratios that differ by 0.12 and waist definitions that differ by four scale points; treating them identically, as categorical systems do, discards exactly the information that determines whether a specific garment will work for each. Replacing labels with continuous scores does not make the assessment more complex for the stylist (four tape measurements and a visual rating take the same time as a categorical assignment) but does make the output more precise, because the algorithm can adjust its recommendations in proportion to the actual values rather than in response to a label boundary.

What the conflict-resolution mechanism contributes is a protocol for situations where practitioner intuition currently operates without guidance. Sixty percent of cases in the follow-up sample produced at least one inter-parameter conflict, meaning that for most clients, at least two of the three parameters disagreed on the optimal direction. Without a resolution mechanism, the stylist must either ignore one parameter, improvise a compromise, or defer to the client's stated preference without knowing whether that preference will hold. By assigning explicit weights and documenting resolution rules for the six most common conflict types, the algorithm converts these moments from ad hoc negotiations into repeatable decisions with trackable outcomes.

What the retention metric contributes is accountability after the consultation ends. Styling has traditionally been evaluated at the point of delivery: does the client approve the outfit? Approval at delivery, however, does not predict use over time. A garment that looks right in the fitting room may sit unworn if it conflicts with the client's daily reality. Measuring retention at six months shifts the evaluation window from first impression to sustained integration, exposing failures that point-of-delivery approval conceals and rewarding recommendations that survive contact with real life.

Subsequent research should address the limitations noted above through a prospective controlled design: assigning new clients randomly to three-parameter and single-parameter protocols, measuring retention at six and twelve months via direct wardrobe audit rather than self-report, and using the accumulated data to empirically calibrate the default parameter weights. Cross-cultural testing with non-Western populations would establish whether the dimensional scales and conflict typology transfer across fashion systems with different aesthetic norms. Computational modelling of the algorithm, using client data to train a recommendation engine that approximates the weighted matrix, could eventually make the framework available at scale through digital platforms, moving it from the consulting room into the daily decision-making of anyone building a wardrobe.

References

1. Connell L. J., Ulrich P. V., Brannon E. L., Alexander M., Presley A. B. Body Shape Assessment Scale: Instrument Development for Analyzing Female Figures. *Clothing and Textiles Research Journal*. 2006. Vol. 24, № 2. P. 80–95.

2. Lee J. Y., Istook C. L., Nam Y. J., Park S. M. Comparison of body shape between USA and Korean women. *International Journal of Clothing Science and Technology*. 2007. Vol. 19, № 5. P. 374–391. DOI: https://doi.org/10.1108/09556220710819555

3. Song H. K., Ashdown S. P. Female Apparel Consumers' Understanding of Body Size and Shape: Relationship Among Body Measurements, Fit Satisfaction, and Body Cathexis. *Clothing and Textiles Research Journal*. 2013. Vol. 31, № 3. P. 143–156.

4. Mpampa M. L., Azariadis P. N., Sapidis N. S. A new methodology for the development of sizing systems for the mass customization of garments. *International Journal of Clothing Science and Technology*. 2010. Vol. 22, № 1. P. 49–68. DOI: https://doi.org/10.1108/09556221011008802

5. Itten J. *The Art of Color: The Subjective Experience and Objective Rationale of Color*. New York : Van Nostrand Reinhold, 1961. URL: https://openlibrary.org/books/OL5824199M/The_art_of_color .

6. Jackson C. *Color Me Beautiful: Discover Your Natural Beauty Through the Colors That Make You Look Great and Feel Fabulous!*. New York : Ballantine Books, 1981. URL: https://archive.org/details/colormebeautiful00jack

7. Hong H. R., Kim Y. I. A mobile application for personal colour analysis. *Cogent Business & Management*. 2019. Vol. 6, № 1. Article 1576828.

8. Munsell A. H. *A Color Notation*. Boston : Geo. H. Ellis Co., 1905. URL: https://www.gutenberg.org/ebooks/26054.

9. Elliot A. J., Maier M. A. Color Psychology: Effects of Perceiving Color on Psychological Functioning in Humans. *Annual Review of Psychology*. 2014. Vol. 65. P. 95–120. DOI: https://doi.org/10.1146/annurev-psych-010213-115035.

10. Li Q., Zhao J., Xue Z., Zeng X. A systematic approach to learning and identifying personality tendencies of consumers for individualized fashion product development. *Textile Research Journal*. 2024. Vol. 94, № 15–16.

11. Buether A. Color Psychology and Personality Perception: A Study on the Connection Between Clothing Colors and Personality Traits. Zenodo, 2025. DOI: https://doi.org/10.5281/zenodo.16846010

12. Costa P. T., McCrae R. R. *Revised NEO Personality Inventory (NEO PI-R) and NEO Five-Factor Inventory (NEO-FFI): Professional Manual*. Odessa, FL : Psychological Assessment Resources, 1992. URL: https://books.google.com/books/about/Revised_NEO_Personality_Inventory_NEO_PI.html?id=mp3zNwAACAAJ.

13. Kwon Y. H. The Influence of Appropriateness of Dress and Gender on the Self-Perception of Occupational Attributes. *Clothing and Textiles Research Journal*. 1994. Vol. 12, № 3. P. 33–39. URL:: https://www.semanticscholar.org/paper/The-Influence-of-Appropriateness-of-Dress-and-on-of-Kwon/ea95d10f49444d2efc849acd1ec6b559881d4a57

14. Saaty T. L. *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. New York : McGraw-Hill, 1980. URL: https://archive.org/details/analytichierarch0000saat .

15. Ræbild, U., and Bang, A. (2018) The Fashion Collection Recalibrated - A Design Tool Furthering Sustainable Strategies, in Storni, C., Leahy, K., McMahon, M., Lloyd, P. and Bohemia, E. (eds.), Design as a catalyst for change - DRS International Conference 2018, 25-28 June, Limerick, Ireland. https://doi.org/ 10.21606/drs.2018.53