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Technology Acceptance of AI-Pre-Filled Carts in Online Grocery Retailing: Testing TAM Paths and Their Link to Objective Performance

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Abstract

Online grocery retailing remains effort-intensive because consumers must coordinate many item-level decisions, making basket construction and correction a key barrier to more frequent use. This study examines consumer acceptance of an AI-pre-filled basket in Austrian online grocery retailing and links Technology Acceptance Model (TAM) mechanisms to objective interaction performance. Using a field-proximate one-group pre–post design, participants edited an AI-pre-filled basket in a standardized online shop and completed pre- and post-task surveys using 0–100 slider scales; log data captured processing time and edit actions. Analyses are based on n = 297 valid cases. Results show a substantial and statistically significant within-person increase in online grocery usage intention after the AI-basket interaction, rising from 39.17 to 59.78. The TAM results support the core mechanism: perceived ease of use is positively associated with perceived usefulness, and perceived usefulness strongly predicts behavioral intention, whereas a direct ease-of-use effect on intention is not supported. Linking perceptions to log data shows that acceptance is more strongly associated with correction demand than with processing time. AI-basket acceptance depends less on speed than on reducing rework while preserving user control; retailers should therefore design AI baskets as controllable, editable, low-rework systems rather than speed-oriented automation tools.

Keywords: online grocery; AI-pre-filled basket; Technology Acceptance Model; log data; editing effort; Austria

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1. Introduction

Online grocery retailing has become an established component of digital retailing, yet its everyday use remains limited by category-specific barriers. Unlike many other e-commerce domains, grocery shopping requires consumers to coordinate recurring, multi-item, and often household-specific decisions within a single shopping episode. As a result, continued use depends not only on general digital readiness, but also on whether the online channel reduces perceived effort, uncertainty, and process friction in comparison with established offline routines [1–10]. Recent European evidence further shows that attitudes and purchase intentions in online grocery shopping are shaped by innovation-related attributes as well as consumption- and food-related motives, and that consumers cannot be characterized as a homogeneous group [5]. In Austria, e-commerce is generally well-established; nevertheless, this does not automatically translate into high usage, specifically

in online grocery retailing, particularly because process costs such as search, selection, substitutions, and quantity planning remain especially salient in this domain [7–10].

A central challenge in online grocery lies in the structure of the shopping task itself: grocery purchases are often routinized (e.g., weekly stock-up trips, repeat purchases), yet they are also detail-intensive because many individual decisions must be made and coordinated. This creates search and editing effort as well as cognitive load, which may be perceived more strongly in the digital channel than in brick-and-mortar shopping [7,10].

At the same time, retail interfaces are increasingly shaped by AI-based personalization, recommendation, and automation functions. In online grocery retailing, such functions are particularly relevant because they can support not only individual product discovery, but also the construction of entire baskets [11]. This shifts the role of AI from a narrow recommendation tool toward a more active form of decision support: the system does not merely suggest additional products, but provides a modifiable starting point for a complex shopping task. However, this stronger form of assistance also raises acceptance-related questions, because consumers must evaluate not only whether the AI output is useful, but also whether it remains understandable, controllable, and easy to correct.

Accordingly, technological assistance functions have attracted attention—not only those that recommend single products, but also those that actively support recurring shopping logics. In recommender-systems research, a substantial algorithmic stream addresses this need: "next-basket" and (within-/next-) basket recommenders model purchase histories to predict future baskets or basket components [11–13]. However, this literature is predominantly technical (predictive performance, scalability, model architecture) and offers limited evidence on how consumers accept automated, "delegating" shopping support during a realistic purchasing process [11–13].

Against this backdrop, an AI-pre-filled basket represents a particularly far-reaching assistance function: rather than recommending individual items, the system provides a pre-assembled shopping proposal that users can review, adapt, and finalize. Conceptually, this promises to reduce key process frictions in online grocery by partially automating routine decisions and minimizing the effort required for search and basket construction [7,10]. At the same time, especially for a pre-filled basket, it remains unclear whether consumers interpret the functional gain as a loss of control or perceive it as an increase in convenience and efficiency. Prior evidence on algorithmic decision autonomy and recommendation interfaces suggests that autonomy and perceived control can be pivotal for the acceptance of algorithmic support [14,15]. Acceptance therefore becomes pivotal: even highly capable systems will have no market impact if users do not experience them as useful and easy to use.

To explain such acceptance mechanisms, the Technology Acceptance Model (TAM) provides an established theoretical reference framework [16]. TAM posits that the perceived ease of use (PEOU) supports perceived usefulness (PU), and that PU and PEOU shape behavioral intention to use (BI) [16]. In online grocery contexts, empirical work repeatedly highlights perceived usefulness as central for intention/acceptance, and Austria-specific evidence similarly points to PU as a key determinant in the online grocery setting [6,17].

Nevertheless, an important research gap remains when AI-pre-filled baskets are considered as a concrete retail function. Existing acceptance research typically focuses on subjective evaluations, such as perceived usefulness, the perceived ease of use, and behavioral intention, whereas technical recommender-system research often emphasizes objective system or interaction indicators, such as prediction quality, efficiency, or recommendation performance [11–13,16]. For AI baskets, these two levels should be conceptually and empirically distinguished rather than treated as interchangeable. Subjective acceptance indicators capture how users evaluate the AI-supported shopping experience, while objec-

tive performance indicators capture observable interaction outcomes, such as processing time, editing effort, and the extent to which users retain or modify the AI-generated basket. This distinction is important because objective efficiency does not necessarily translate directly into perceived usefulness or behavioral intention. For example, a basket may be completed quickly but still be perceived as poorly fitting if many corrections are required; conversely, a longer interaction may still be evaluated positively if the basket is experienced as useful, controllable, and easy to adapt. Linking these two levels therefore allows this study to examine whether observable process performance is reflected in subjective acceptance evaluations.

Building on this distinction, this study investigates an AI-pre-filled basket in the Austrian online grocery retailing context and links TAM-based acceptance mechanisms with objective interaction performance indicators. Its novelty lies in integrating two perspectives that are often treated separately. Traditional TAM-based studies explain acceptance primarily through subjective perceptions such as perceived usefulness, the perceived ease of use, and behavioral intention [16], and this logic has also been applied in online grocery contexts [1,6,17]. Technical recommender-system studies, by contrast, often evaluate basket recommendations mainly through system-oriented performance perspectives, including prediction quality, model architecture, or next-basket recommendation accuracy [11–13]. The present study connects these perspectives within one empirical design by relating consumers' post-task acceptance evaluations to observable interaction outcomes, including editing effort and processing time. Empirically, the study addresses this aim in three steps: first, it examines whether experiencing an AI-pre-filled basket is associated with a within-person increase in online grocery usage intention; second, it tests the core TAM relationships after the AI-basket interaction; and, third, it links subjective acceptance evaluations to log-based performance indicators.

The study therefore contributes to the literature theoretically by using TAM as the perceptual core of an integrated framework and extending it with performance-, fit-, and control-oriented perspectives relevant to AI-enabled basket-level decision support, methodologically by combining survey-based acceptance measures with log-based interaction data, and practically by identifying correction demand and editability as central design levers for AI-basket acceptance. In doing so, AI-pre-filled baskets are not assessed merely as a technical recommendation problem, but as an experienced consumer decision-support process in which perceived value, usability, correction demand, objective performance, and user control jointly shape acceptance. This yields the following research questions:

RQ1. Acceptance: How strong is consumers' behavioral intention to use AI baskets in Austrian online grocery retailing, and how does online grocery usage intention change after interaction with an AI-pre-filled basket?

RQ2. Ease of use and usefulness (TAM): To what extent do the perceived ease of use and perceived usefulness explain behavioral intention to use the AI-basket function after the AI-basket interaction?

RQ3. Relationship between TAM and performance: Is there a positive correlation between TAM indicators and better objective performance of AI baskets?

2. Conceptual Framework: AI Baskets and Consumer Behavior in Online Grocery Retailing

Online grocery retailing differs from other e-commerce categories in several key respects: purchases are high-frequency, consist of many items, and partially follow routinized patterns (e.g., recurring staple needs), while situational factors (promotions, availability, meal planning) also play a role [18]. As a result, online grocery involves less a single

purchase decision for one product and more a complex bundled decision about an entire shopping basket [18]. In practice, cognitive and time burdens are concentrated in basket construction (searching, filtering, planning quantities, comparing alternatives), which can function as a barrier to (increased) usage [7,9]. Correspondingly, research on online grocery behavior indicates that acceptance and usage intention are closely linked to consumers' subjective evaluation of the digital shopping experience, including perceived usefulness and the perceived ease of use [1,17].

2.1. Conceptual Background and Theoretical Positioning

Against this background, an AI-pre-filled basket can be conceptualized as a specific form of basket-wise recommendation (basket recommendation): rather than suggesting individual items, the system proposes a (partly) complete set of products that the user can then adopt, modify, or reject. From a technical perspective, next-basket recommendation is established as a distinct problem class within the recommender-systems literature because it addresses sequences of baskets and complementary basket logics rather than predicting isolated item preferences [11–13]. In the consumer context, a second perspective is relevant: a pre-filled basket also functions as a choice-architecture instrument in the sense of a default option (i.e., a pre-set but modifiable starting point). Evidence from online grocery interventions suggests that such default settings in digital baskets can measurably influence actual purchasing behavior and basket composition [19,20]. In addition, recent empirical work indicates that pre-filled online baskets/carts are feasible and acceptable within specific target groups, underscoring the approach's relevance as a low-threshold form of shopping support [21,22].

Because AI-pre-filled baskets combine automation, recommendation, and user-controlled adaptation, their acceptance cannot be fully captured by a generic technology-adoption perspective alone. TAM provides the perceptual core for explaining how the perceived ease of use and perceived usefulness shape behavioral intention [16,23–25]. However, the AI-basket context also requires complementary theoretical perspectives. Task–Technology Fit explains why the usefulness of the function should depend on whether the AI output matches the task requirements of basket construction and reduces observable process burden [26]. The IS success perspective further suggests that system and output quality are linked to usage-related outcomes through perceived benefits [27]. Finally, research on algorithm aversion, appreciation, and user control highlights that consumers' reactions to AI suggestions depend not only on average performance, but also on perceived errors, modifiability, and the ability to override or adapt algorithmic outputs [15,28–31]. The present framework therefore treats TAM as the acceptance core, but embeds it in a broader AI-specific logic of task fit, objective performance, editability and controllable adaptation.

This study positions the functionality within the broader literature on consumers' acceptance of new technologies and uses TAM as the central perceptual component of a broader AI-basket framework. TAM explains behavioral intention through two central perception constructs: perceived usefulness (PU) and the perceived ease of use (PEOU) [16]. PEOU typically affects PU, both influence behavioral intention (BI), and PEOU may also exert a direct effect on BI [16,24,25]. This perspective is particularly plausible in online grocery retailing because the perceived usefulness of an AI function (e.g., time savings, reduced planning effort, better basket fit) and its perceived ease of use (e.g., comprehensibility, low interaction effort, ease of correction) directly target the core task of "building a shopping basket." Empirical TAM applications in online grocery contexts report consistent relationships between PU/PEOU and behavioral intention [1,6,17]. In the present design, acceptance is captured not only as intention to use the AI function itself, but also as a potential change in online grocery usage intention after the AI-basket interaction.

A conceptually important contribution of this study is the linkage of subjective TAM indicators with objective performance. While TAM is traditionally perception-based, the present approach addresses whether better actual performance of AI baskets is associated with higher PU/PEOU/BI values. This bridge can be theoretically grounded in performance-oriented information-systems perspectives, particularly Task–Technology Fit (TTF): information systems generate performance effects when functionality matches task requirements; TTF is linked to both usage and individual performance [26]. In addition, IS success models argue that system/output quality and resulting benefits are connected to use (or the intention to use) and related usage outcomes [27]. In this study, "objective performance" is operationalized via observable indicators (e.g., time, editing effort/number of adjustments, adoption of suggestions, and an equally weighted performance index as an aggregate measure). Thus, TAM is not replaced but complemented by a behavioral validation: if the AI demonstrably reduces effort or improves basket fit, this should—under plausible conditions—be reflected in higher perceived usefulness and ease of use, and consequently in higher usage intention [26,27].

Finally, in consumer contexts of AI-based recommendations, acceptance may depend not only on average system performance but also on psychological reactions to algorithmic suggestions. Research on algorithm aversion shows that people may reject algorithmic support more strongly than human support after observing errors, even when algorithms are superior on average; conversely, the literature also documents algorithm appreciation under certain conditions [28–30]. For AI baskets, the degree of control and modifiability is particularly relevant: if users can easily adjust system suggestions, acceptance barriers may be reduced [15,30,31]. In the present setting, this consideration is embedded conceptually via the user's ability to edit the pre-filled basket and informs the interpretation of PEOU and PU.

2.2. AI Basket and Increased Usage Intention in Austrian Online Grocery Retailing (H1)

In online grocery retailing, even small reductions in search, selection, and planning effort can serve as key levers to move (non-)users toward (more frequent) usage [7,9,10]. An AI-pre-filled basket can be understood both as a friction reducer and as a choice-architecture intervention: it shifts the starting point of the shopping process from an empty basket to a curated pre-selection, thereby lowering cognitive costs, decision effort, and perceived time scarcity [19,21,23]. Evidence from online grocery settings shows that default options within the basket can measurably change actual purchasing behavior (e.g., higher spending and/or shares for pre-set items), underscoring the relevance of the mechanism of a "given pre-selection" in realistic online shopping situations [20]. In addition, findings on personalized, pre-filled online baskets suggest that such an approach can be feasible and acceptable to consumers [21]. Against this background, in the Austrian online grocery context, providing an AI basket is expected to increase usage intention [1,5,6].

H1: *Online grocery usage intention is higher after interaction with an AI-pre-filled basket than before the interaction.*

2.3. Perceived Ease of Use as a Driver of Perceived Usefulness (H2)

The Technology Acceptance Model (TAM) argues that technologies are evaluated as useful when they can be used without substantial learning or operating effort [16,24,25]. The perceived ease of use (PEOU) thus acts not merely as a usability attribute but as a cognitive enabling factor: the lower the expected effort, the more likely the system is to be seen as suitable for supporting goal attainment [16,24,25]. In TAM, this logic is captured by the central path PEOU → PU and has been extensively supported empirically [16,24,25]. Applied to AI baskets, this implies that, when consumers experience the process of adopting,

adjusting, and finalizing a pre-filled basket as intuitive, they are more likely to evaluate the AI basket as functionally useful (e.g., for saving time, simplifying planning, reducing errors) [7,9,26].

H2 (TAM): *Perceived ease of use (PEOU) is positively associated with perceived usefulness (PU).*

2.4. Perceived Usefulness as the Core Predictor of Behavioral Intention (H3)

Within TAM, perceived usefulness (PU) is the strongest immediate cognitive predictor of behavioral intention (BI) because it captures the instrumental value added by a technology [16,24,25]. For AI baskets in online grocery retailing, PU is particularly relevant when consumers experience the concrete output as "effort-saving": less search effort, fewer correction loops, faster completion of a needs-appropriate basket, and overall higher task attainment (e.g., a better-fitting basket given stated preferences) [7,9,26]. In consumer e-commerce contexts, PU is also considered a robust acceptance criterion because usefulness evaluations often translate directly into reuse and recommendation intentions [16,24,25].

H3 (TAM): *Perceived usefulness (PU) positively predicts behavioral intention (BI) to use the AI-basket function.*

2.5. Direct Effect of Perceived Ease of Use on Behavioral Intention (H4)

Beyond its indirect effect via PU, TAM also posits a direct path from PEOU to BI: even if a system's benefits are recognized, perceived complexity can suppress behavioral intention; conversely, a high ease of use can facilitate adoption even independent of perceived usefulness [16,24,25]. In online grocery retailing, this mechanism is plausible because shopping often occurs under everyday constraints (time pressure, routines, low involvement) [1,6,9,10]. An AI basket that is experienced as "easy to adopt and easy to correct" reduces the entry barrier and can therefore strengthen behavioral intention directly [16,30,31]. The relevance of effort-related expectations (effort components) is also emphasized in context-specific acceptance models for e-grocery [1,17].

H4 (TAM): *Perceived ease of use (PEOU) is directly positively associated with behavioral intention (BI) to use the AI-basket function.*

2.6. Objective AI-Basket Performance and Perceived Usefulness (H5)

A distinctive feature of this study is the linkage of subjective TAM evaluations with objective performance measures of the AI basket (including a performance index as well as indicators such as adoption/hit aspects and time components) [16,26,27]. Conceptually, this relationship can be grounded in two established IS perspectives. First, Task–Technology Fit emphasizes that performance effects arise when system capabilities match task requirements: better fit/performance increases perceived usefulness [26]. Second, IS success models argue that quality/performance (e.g., output quality) supports usage intentions via perceived benefits and satisfaction [27]. For AI baskets, this implies that, the better the AI output fulfills the shopping task (e.g., more relevant product selection, fewer unsuitable suggestions, a basket closer to the goal), the higher PU should be [11–13,26,27].

H5 (Performance → PU): *Higher objective AI performance is positively correlated with perceived usefulness (PU).*

2.7. Objective Performance and Perceived Ease of Use (H6)

Although PEOU is primarily conceptualized as an interaction attribute, in practice, it is closely tied to output quality: when a system "gets it right," the required correction

and search effort decreases, making usage subjectively feel easier [16,24–26]. User-centered recommender-system frameworks capture this chain by explaining user reactions through objective system characteristics (e.g., accuracy/quality) via experienced value dimensions (including convenience and utility) [11,32]. More recent work on algorithm experience similarly suggests that perceived accuracy is linked to experienced convenience/utility—and thus to a key component of what consumers interpret as "effortless" [14,15,32]. Transferred to AI baskets, higher objective performance is therefore expected to be associated with higher PEOU, because less rework and fewer search steps are required [7,11–13,26].

H6 (Performance → PEOU): *Higher objective AI performance is positively correlated with the perceived ease of use (PEOU).*

2.8. Objective Performance and Behavioral Intention (H7)

Finally, objective performance gains are expected to translate not only via PU/PEOU but also directly into behavioral intentions: consumers infer a higher likelihood of success and lower error costs from "better-functioning" systems, increasing willingness to (re-)use them [16,26,27]. In studies on AI-based recommender systems in online shopping, behavioral intention is supported by perceived technology/personalization quality [14,15,32]. IS success models further suggest that quality and benefit effects culminate in usage-related outcomes (with intention to use as a central success dimension) [27]. For the present application, this implies that a higher objective performance of the AI basket should be associated with stronger behavioral intention (BI) [11–13,26,27].

H7 (Performance → BI): *Higher objective AI performance is positively correlated with behavioral intention (BI).*

Overall, the hypothesis development follows the three research questions: H1 addresses RQ1, H2–H4 address RQ2, and H5–H7 address RQ3.

Based on the theoretical arguments developed above, Figure 1 summarizes the conceptual model of the study, including the pre–post acceptance shift, the TAM relationships, and the links between objective performance and acceptance indicators.

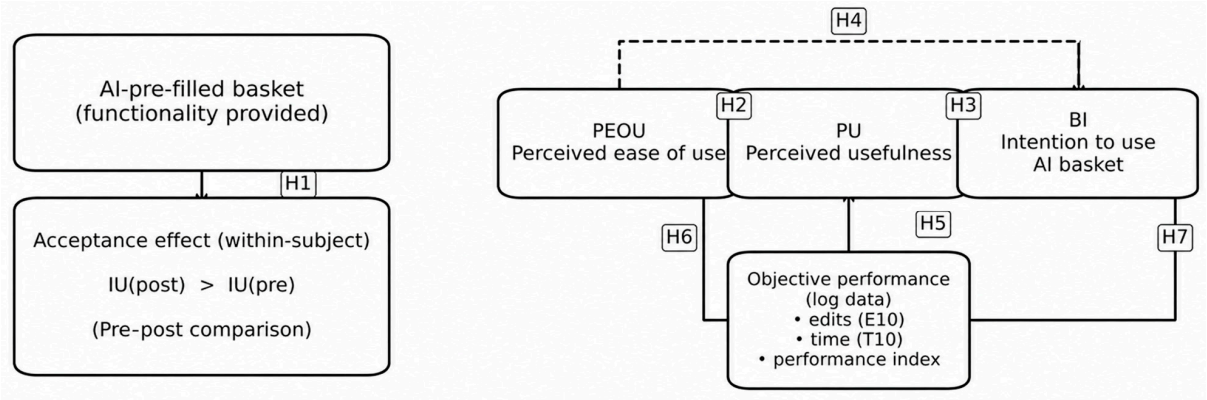


Figure 1. Conceptual model and hypothesized relationships. Notes: PEOU = perceived ease of use; PU = perceived usefulness; BI = behavioral intention to use the AI-basket function; IU = increased online grocery usage intention. PEOU, PU, and BI were measured post-task; objective performance was derived from log data.

3. Methods

3.1. Study Design and Data Collection Procedure

To examine the consumer acceptance of AI-generated baskets in Austrian online grocery retailing, a field-proximate, standardized one-group design was implemented. Data collection was conducted via in-person recruitment in the vicinity of brick-and-mortar grocery shopping (passers-by on their way to shop) across multiple Austrian cities. This deliberately embedded the study in a realistic decision context in which shopping intentions and household requirements are immediately salient.

Before participation, potential respondents were informed about the purpose and procedure of the study, the voluntary nature of participation, the anonymous processing of the collected survey and interaction data, and their right to discontinue participation at any time. Only individuals who agreed to participate were included in the study.

To ensure procedural consistency, all persons involved in data collection followed a standardized data collection protocol. Interviewers were instructed in advance regarding participant approach, an explanation of the study purpose, informed consent procedures, task handover, and the standardized measurement procedure used throughout the field phase.

The procedure consisted of three sequential phases: (1) pre-assessment of the shopping context, (2) interaction with an online basket pre-filled by the AI, and (3) a post-experiment survey assessing acceptance and usage intentions. In the pre-assessment, participants completed a short questionnaire capturing shopping-relevant characteristics (e.g., household size, preferences, dietary habits, and selected conditions of the upcoming shopping trip). In addition, online grocery usage intention without a pre-filled basket was measured as a reference. The explicit goal was not to elicit concrete product lists, but to structure the contextual signals required to parameterize AI-based basket generation in a plausible manner.

Based on these inputs, an AI-generated basket was created using the product assortment of an established Austrian online grocer (the same shop for all participants) as the product universe, and the basket was pre-filled within the online shop. The task started with handing over the fully generated basket to the participant. Participants were then asked to edit the basket so that it would match their intended purchase as closely as possible. The interaction took place on provided, largely identical laptops; the internet connection was stable, and the procedure was standardized via a uniform setting. A small in-kind incentive was offered to facilitate participation.

The editing process ended once participants stated that the basket was "finished." Each basket interaction (e.g., adding, removing, replacing products) was recorded as an edit action and logged together with the processing time (log data). This approach enables linking subjective acceptance measures (post-survey) to objective usage and performance indicators (log data) within the same empirical episode.

Before the main field phase, the questionnaire, task instructions, AI-basket procedure, and logging process were pretested with a small number of participants to assess comprehensibility, technical functionality, and procedural consistency. Based on the pretest, minor wording and procedural adjustments were made before the final data collection.

The standardized study procedure, including the main data sources and the derivation of the final analysis sample, is summarized in Figure 2.

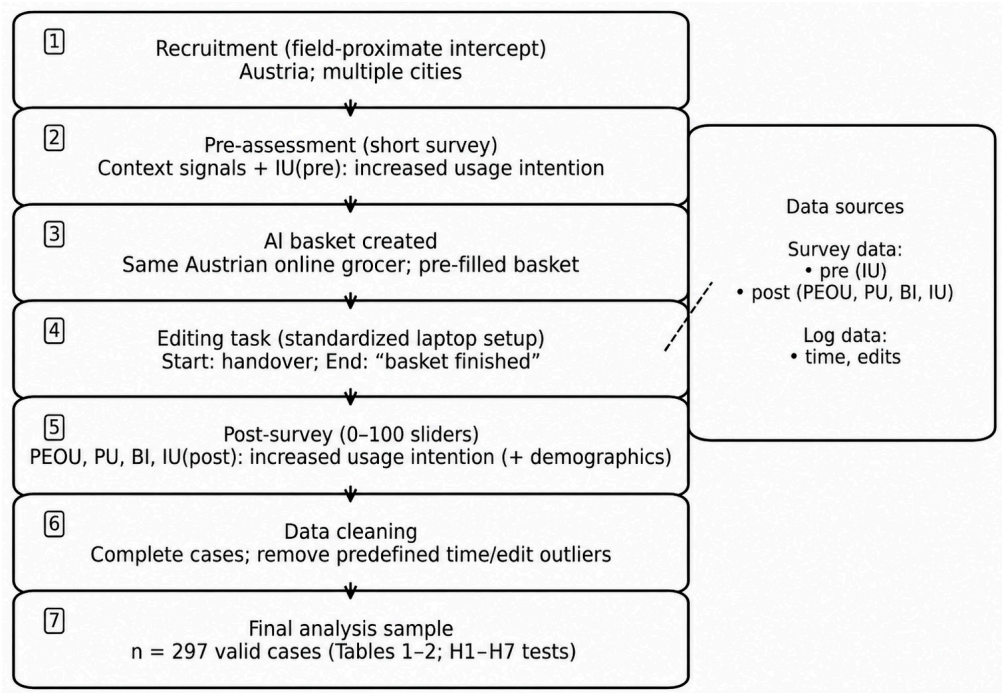


Figure 2. Study procedure, data sources, and final analysis sample.

3.2. Measures

3.2.1. Measurement Model and Operationalization

This study combines a TAM-based acceptance model with objective performance indicators of the AI basket solution. In this study, subjective constructs refer to self-reported perceptions and intentions collected through the survey instrument, whereas objective performance indicators refer to log-based behavioral measures recorded during the basket-editing task. This distinction enables the analysis to examine whether users' evaluations of the AI basket correspond to observable interaction outcomes. Acceptance is conceptualized not merely as "liking," but as intention to use and intention to increase usage in online grocery retailing—i.e., a behavior-proximal outcome.

The measurement of the core acceptance constructs was based on established TAM measurement logic. The items for perceived ease of use, perceived usefulness, and behavioral intention were adapted from Davis [16], Venkatesh and Davis [24], and Venkatesh and Bala [25], and adjusted to the specific context of AI-pre-filled grocery baskets. The items measuring increased online grocery usage intention were formulated in line with the study context to capture the expected change in future online grocery use after experiencing the AI-pre-filled basket.

Acceptance: Increase in Online Grocery Usage Intention

To capture a potential intention shift in line with research question RQ1, online grocery usage intention was measured using a within-subject pre–post design. Immediately before interacting with the AI-pre-filled basket (pre-assessment) and directly afterward (post-experiment), participants answered two content-parallel items on the future use and/or intended usage frequency of online grocery retailing. For each measurement occasion, item means were computed from the respective item pair. Hypothesis H1 is tested inferentially using a paired-samples t-test comparing pre- and post-measurements; a significantly higher post-intervention mean is interpreted as evidence of increased usage intention. This operationalizes acceptance not only as absolute approval of the function, but as an empirically observable within-person shift in usage intention immediately following a realistic interaction with the AI tool.

Core TAM Constructs: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU)

Unlike online grocery usage intention, which was measured before and after the AI-basket interaction, the TAM constructs were assessed once after the task. This was done because the perceived ease of use, perceived usefulness, and behavioral intention toward the AI-basket function require a concrete usage experience as their reference point. Accordingly, H2–H4 do not test within-person increases over time, but post-task relationships among the TAM constructs.

PEOU and PU were each measured with four items (peou_01–peou_04; pu_01–pu_04) and aggregated as mean scales (peou_mean; pu_mean). Negatively worded items were transformed via reverse coding (100 − item value) to ensure a consistent direction across scales. This reflects the classic TAM mechanism in which PEOU supports PU and both constructs explain behavioral intention.

Behavioral Intention to Use the AI-Basket Function (BI) as Proximal Acceptance

Participants' immediate behavioral intention regarding AI baskets was measured with five items (bi_01–bi_05) and aggregated into a scale mean (bi_mean). Conceptually, BI serves as the proximal intention outcome, whereas IU captures the strategically relevant (and emphasized) increased usage dimension for online grocery retailing overall.

3.2.2. Objective Performance/Interaction Effort (Log Data)

To operationalize the "performance" of the AI basket (RQ3), three blocks of log-based indicators were used:

1. **Time expenditure:** processing time in seconds and a time metric standardized per ten products (T10).
2. **Editing effort:** total number of edits (edit total) and an edit metric standardized per ten products (E10). Edit types were additionally differentiated (e.g., add/remove/replace actions, as recorded in the dataset).
3. **Content-related fit:** adoption rate and hit rate were computed ex post. The adoption rate reflects the share of AI-suggested products that remained in the final basket; the hit rate captures those AI products that were not only adopted but also remained "accurate/stable" in the final basket according to the defined product-matching criterion.

A performance index was then constructed from time and editing effort: time and edit metrics were log-transformed (to reduce typical right skew), subsequently z-standardized, and aggregated as a negative mean. Higher index values thus indicate better performance (lower time and editing effort given the same task requirements). This operationalization constitutes the central objective performance measure for hypothesis tests on the relationship between TAM indicators and performance (RQ3).

3.2.3. Response Format and Scale Construction

All subjective items were collected using 0–100 slider scales to enable fine-grained judgments and intuitive interpretation (higher values = stronger agreement). Scales were computed as means and additionally z-standardized (. . ._z) to improve comparability in regression models.

3.2.4. Data Cleaning and Analysis Strategy

As part of the preparatory data-quality procedures, the pretest was used to assess the comprehensibility of the questionnaire items, the feasibility of the task procedure, and the correct recording of the log-based performance indicators before the main field phase.

Only complete cases were included in the analyses. In addition, pre-defined exclusion criteria were applied to remove outliers and invalid interactions (notably, extremely long

processing times and/or unusually high edit counts indicative of interruptions or misunderstandings). This procedure supports internal validity, as the core performance logic of the design is interpretable only under consistent task execution.

Hypotheses were tested along two complementary analytical tracks:

1. **Acceptance and TAM relationships (RQ1, RQ2):**
   - Acceptance (RQ1/H1) as pre–post change in online grocery usage intention (IU): acceptance is operationalized as the change in online grocery usage intention immediately following interaction with the AI-pre-filled basket. For this purpose, scale means were computed from the two items before (IU_pre_01, IU_pre_02) and after (IU_post_01, IU_post_02) the task (IU_pre_mean; IU_post_mean). H1 is tested via a t-test comparing the pre and post means (expected: IU_post_mean > IU_pre_mean).
   - TAM relationships (RQ2) via BI: behavioral intention to use the AI-basket function (BI) is explained in line with TAM hypotheses using linear regression models, in which BI is predicted by PU and PEOU; additionally, the core TAM path is modeled with PU predicted by PEOU (PEOU $\rightarrow$ PU). These models are based on post-task TAM measurements and are therefore interpreted as association/prediction models rather than as pre–post change models. For comparability, models are evaluated using both unstandardized coefficients and z-standardized specifications.
2. **Relationship between TAM indicators and objective performance (RQ3):**
   - To test performance-related hypotheses, correlations and linear regression models are estimated between objective performance measures (editing effort and time expenditure) and TAM constructs (PU, PEOU, BI). Performance measures are used as defined in the dataset (including log transformations, standardization, and normalization per ten products where applicable).
   - This tests whether objectively "better" AI baskets (i.e., lower editing effort and lower time expenditure) are systematically associated with higher perceived usefulness, a higher perceived ease of use, and stronger behavioral intention toward the AI function.

Overall, this analytical setup enables consistent answers to the research questions by (i) testing acceptance in online grocery retailing as a pre–post change in usage intention (IU), (ii) testing TAM mechanisms for explaining behavioral intention toward the AI function (BI), and (iii) examining whether subjective evaluations (PU/PEOU/BI) are systematically related to the objective performance dimension of AI baskets.

3.3. Data Analysis

The data analysis follows a two-stage logic. First, the sample characteristics, scale properties, and bivariate relationships are reported. Second, the hypotheses are tested using inferential statistics. The acceptance hypothesis (H1) operationalizes a within-person change in online grocery usage intention as a pre–post difference and is therefore tested using a paired-samples t-test. For the TAM hypotheses (H2–H4) and the performance-related hypotheses (H5–H7), linear regression models and correlations are estimated. To ensure comparability across different scales and metrics, models are evaluated—depending on the hypothesis/specification—using both unstandardized coefficients and z-standardized specifications. For objective performance measures, the transformations defined in the dataset are retained (in particular, log-transformations and z-standardization, as well as standardization to ten products for time and edit metrics). Data preparation, scale construction, and the statistical analyses were conducted using Microsoft Excel.

4. Results

4.1. Sample and Data Cleaning

Data were collected in a field-proximate setting using intercept recruitment in several Austrian cities. Participants were approached immediately before a real grocery shopping trip and first completed a short pre-shopping questionnaire capturing shopping-relevant contextual information (e.g., household size, preferences, stock levels). Based on these inputs, an AI-generated basket was pre-filled in the same Austrian online grocery shop and provided to participants as the initial state. The task was to edit the pre-filled basket until it matched participants' intended purchase to their personal satisfaction; task start and end were defined in a standardized way (start: handover of the generated basket; end: explicit statement that the basket was "finished"). All interactions were captured as log data (time, edit actions, add/remove/replace, etc.). Subsequently, a post-experiment questionnaire (0–100 sliders) was administered; items were aggregated into scales (including PEOU, PU, BI, and increased usage intention for online grocery retailing, IU). Cases that violated pre-defined plausibility and exclusion criteria (e.g., extremely long processing times or extreme edit values) were removed. The analyses are based on $n = 297$ valid cases.

Because the pre-assessment, basket-editing task, and post-task survey were completed within a single study session, the design did not involve longitudinal attrition between measurement waves. Cases were included only if the required pre-task, interaction-log, and post-task data were available and if the interaction met the predefined plausibility criteria. Thus, potential dropout was handled through complete-case inclusion and the exclusion of incomplete or invalid interactions.

In addition to the acceptance and interaction data, this study collected selected demographic characteristics of the final sample, including age, gender, household size, and residential context, distinguishing between central and peripheral locations. To assess whether the main findings were systematically associated with these demographic characteristics, these variables were additionally examined in relation to the central acceptance and performance-related indicators. No statistically significant associations were identified for age, gender, household size, or residential context. Accordingly, the observed acceptance and performance-related findings do not appear to be systematically driven by the demographic characteristics measured in this study.

4.2. Descriptive Results and Correlation Structure

Because usage intention (use_post, use_pre) constitutes this study's central acceptance criterion, this variable is first described descriptively. The post scale mean lies clearly above the neutral midpoint of the scale. Internal consistencies of the multi-item scales are in the acceptable-to-good range: PEOU $\alpha = 0.826$, PU $\alpha = 0.811$, BI $\alpha = 0.871$. Usage intention also shows robust reliability (use_post: $\alpha = 0.806$), while the pre-measure is—expectedly—somewhat lower but still acceptable (use_pre: $\alpha = 0.739$). The difference between the pre- and post-measure reliabilities should be interpreted in light of the short two-item scale and the different reference situations of the two measurements. Before the task, participants evaluated online grocery usage intention without having experienced the AI-basket function, which likely made the judgment more abstract and heterogeneous. After the task, the same intention assessment was anchored in a concrete usage experience, which may have increased item consistency. Importantly, both alpha values exceed commonly used acceptability thresholds for exploratory research, so the reliability difference does not invalidate the pre–post comparison but should be considered when interpreting the magnitude of the effect.

Table 1 summarizes the descriptive statistics and internal consistencies of the main constructs.

Table 1. Descriptive statistics and internal consistencies of the main constructs.

Construct/Variable	k	Mean	SD	95% CI (Mean)	Cronbach's α
IU_pre_mean	2	39.17	21.21	[36.75; 41.59]	0.739
IU_post_mean	2	59.78	13.75	[58.21; 61.35]	0.806
PEOU_mean	4	69.02	21.60	[66.55; 71.49]	0.826
PU_mean	4	69.02	22.63	[66.44; 71.60]	0.811
BI_mean	5	76.55	18.79	[74.40; 78.70]	0.871

Note: k = number of items; CI = confidence interval; α = Cronbach's alpha; *n* = 297.

Table 2 reports the Pearson correlation matrix for the main acceptance, TAM, and objective performance variables. The correlation pattern is broadly consistent with the theoretical logic of the study. Within the TAM structure, the perceived ease of use is positively correlated with perceived usefulness (r = 0.243), and perceived usefulness shows a strong positive association with behavioral intention to use the AI-basket function (r = 0.528). In contrast, the perceived ease of use is not meaningfully correlated with behavioral intention (r = −0.045), which already indicates that the ease of use may operate primarily through usefulness rather than as an independent intention driver. The objective performance indicators show a differentiated pattern: the aggregated performance index is positively associated with behavioral intention (r = 0.297) and online grocery usage intention (r = 0.201), whereas editing effort, measured as log(E10), is negatively associated with behavioral intention (r = −0.429), perceived usefulness (r = −0.244), and online grocery usage intention (r = −0.377). By contrast, processing time, measured as log(T10), shows only weak associations with the acceptance constructs. This supports the interpretation that correction demand is more relevant for acceptance than pure task duration.

Table 2. Correlation matrix for unstandardized variables.

Construct/Variable	1	2	3	4	5	6	7	8	9	10
1. PEOU	1.000									
2. PU	0.243	1.000								
3. Performance index	0.102	0.161	1.000							
4. log(E10)	−0.134	−0.244	−0.793	1.000						
5. log(T10)	−0.024	−0.004	−0.777	0.233	1.000					
6. Age	0.109	−0.165	−0.047	0.075	−0.002	1.000				
7. Residence	−0.037	0.037	0.015	0.035	−0.060	0.018	1.000			
8. Household size	0.005	0.017	0.113	−0.145	−0.031	−0.086	−0.053	1.000		
9. BI	−0.045	0.528	0.297	−0.429	−0.031	−0.163	0.034	0.020	1.000	
10. IU_Post	0.081	0.328	0.201	−0.377	0.070	−0.017	−0.086	−0.072	0.435	1.000

Note: Pearson correlations are shown in the lower triangle; values are rounded to three decimals. PEOU = perceived ease of use; PU = perceived usefulness; BI = behavioral intention; E10 = editing effort per ten products; T10 = processing time per ten products; *n* = 297.

4.3. Hypothesis Testing

The hypothesis tests follow two different empirical logics. H1 tests a within-person pre–post change in online grocery usage intention. In contrast, H2–H4 examine post-task TAM relationships among the perceived ease of use, perceived usefulness, and behavioral intention to use the AI-basket function. Accordingly, H2–H4 are interpreted as association and prediction hypotheses rather than as within-person change hypotheses. H5–H7 then link the post-task acceptance constructs to objective log-based performance indicators.

H1 (Acceptance/Increased Usage Intention)

H1 tests whether online grocery usage intention is higher after interaction with an AI-pre-filled basket than before the interaction. The hypothesis is tested as a within-person pre–post comparison (n = 297). Descriptively, the mean comparison indicates a clear increase in online grocery usage intention after interacting with the AI basket, with the post measure exceeding the baseline measure. This pattern is corroborated by the inferential test: the paired-samples t-test indicates a highly significant pre–post difference, supporting H1 based on the within-person comparison. Pre and post values are also positively correlated, indicating stable rank-ordering across measurement points (i.e., higher baseline intentions tend to be associated with higher post intentions), without attenuating the observed pre–post increase.

In addition to the paired comparison, H1 was evaluated using a multiple linear regression with z-standardized post-task online grocery usage intention as the dependent variable. The model included acceptance constructs, objective process measures, and covariates (PEOU, PU, BI, editing and time indicators, and demographic controls). It was statistically significant overall and explained a relevant share of variance. At the predictor level, BI and PU showed positive associations, whereas PEOU had no independent effect in the multivariate specification. Beyond subjective constructs, objective process measures contributed as expected: higher editing effort, as a strain-proximal indicator, was negatively associated with post-task intention, while the log-transformed and standardized time indicator showed a positive association. Household size was additionally associated with the dependent variable, whereas age did not emerge as an independent predictor.

The supplementary hypothesis evaluation further reports a difference model explaining the magnitude of change (pre–post) directly. This model does not reach a substantive level of explained variance and is not significant overall. Accordingly, the observed increase in online grocery usage intention is primarily interpreted as a robust level-shift result (paired comparison), while inter-individual differences in the change itself are only weakly captured by the predictors included in the model.

Figure 3 visualizes the within-subject increase in online grocery usage intention from the pre-assessment to the post-task measurement.

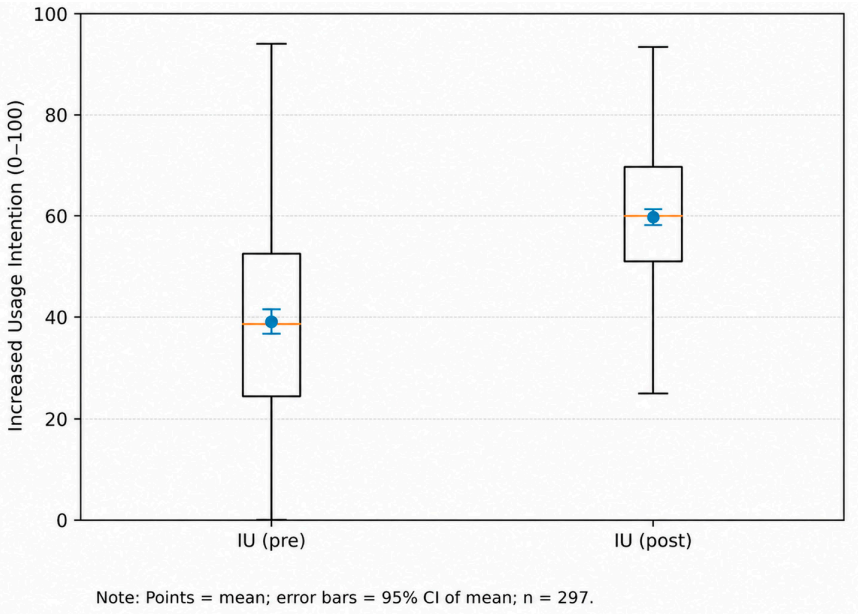


Figure 3. Pre–post comparison of online grocery usage intention.

H2 (PEOU → PU)

For H2, a bivariate linear regression model is estimated (PU as dependent variable; PEOU as predictor; $n = 297$). The relationship is positive and statistically supported ($t = 4.29$; $p < 0.001$). Model fit indicates a moderate explanatory contribution ($R^2 \approx 0.06$; overall model significant: $F(1,295) = 18.43$; $p < 0.001$). Thus, H2 is supported: higher ease-of-use evaluations are associated with higher usefulness evaluations.

H3 (PU → BI)

H3 is tested using a linear regression model (BI as dependent variable; PU as predictor; unstandardized 0–100 scales; $n = 297$). PU shows a clearly positive, highly significant effect on BI ($b \approx 0.44$; $t \approx 10.69$; $p < 0.001$). Explained variance is substantial ($R^2 \approx 0.28$; overall model significant: $F(1,295) \approx 114.32$; $p < 0.001$). The 95% confidence interval for the PU coefficient lies entirely above zero. Hence, H3 is supported.

H4 (PEOU → BI)

For H4, an unstandardized bivariate regression model is estimated (BI as dependent variable; PEOU as predictor; $n = 297$). The coefficient is small and not significant ($b \approx -0.039$; $t \approx -0.78$; $p = 0.436$); explained variance is correspondingly minimal ($R^2 \approx 0.002$; overall model not significant: $F(1,295) \approx 0.61$; $p = 0.436$). H4 is therefore not supported.

H5 (Performance → PU)

H5 examines the relationship between objective performance and perceived usefulness (PU, z-standardized; $n = 297$). In the main model, PU_z is explained by Performance-Index_z (higher values indicate better performance). The coefficient is positive and significant ($b = 0.201$; $t = 2.75$; $p = 0.006$) with a small share of explained variance ($R^2 = 0.025$). An additional component model decomposes performance into editing effort and time: editing effort is significantly negatively associated with PU ($b = -0.257$; $t = -4.43$; $p < 0.001$), whereas the time component is not significant ($p = 0.339$); model fit is higher ($R^2 = 0.062$). Overall, H5 is supported.

H6 (Performance → PEOU)

For H6, the main specification reports a regression model in which PEOU_z is explained by log(E10)_z (editing effort) and log(T10)_z (time) ($n = 297$). The model explains little variance ($R^2 = 0.018$; adj. $R^2 = 0.011$) and reaches a borderline level of significance at the model level ($F(2,294) = 2.72$; $p = 0.068$). At the predictor level, editing effort is significantly negatively associated ($b = -0.136$; $t = -2.30$; $p = 0.022$; 95% CI: $[-0.253; -0.019]$), while the time component shows no independent association ($b = 0.008$; $t = 0.14$; $p = 0.890$). H6 is partially supported: editing effort is significantly negatively associated with PEOU, whereas the overall model remains only marginally significant and processing time shows no independent association.

H7 (Performance → BI)

H7 is tested using a regression model in which BI_z is explained by log(E10)_z and log(T10)_z ($n = 297$). The model is highly significant and explains a relevant share of variance ($R^2 = 0.189$; adj. $R^2 = 0.183$; $F(2,294) = 34.22$; $p < 0.001$). Editing effort is a strong negative predictor of BI ($b = -0.446$; $t = -8.25$; $p < 0.001$), whereas the time component shows no independent effect ($b = 0.073$; $t = 1.34$; $p = 0.180$). An additional evaluation reports an alternative specification using an aggregated performance index, which yields a consistent condensed representation of the relationship. Overall, H7 is supported, with the association in the main model primarily driven by editing effort.

Table 3 summarizes the hypothesis-testing results by reporting the empirical test, main result, and decision for each hypothesis.

Table 3. Summary of hypothesis-testing results.

Hypothesis	Empirical Test	Main Result	Decision
H1: Online grocery usage intention is higher after interaction with an AI-pre-filled basket than before the interaction.	Paired-samples comparison of IU_pre_mean and IU_post_mean	IU increased from 39.17 before the AI-basket interaction to 59.78 after the interaction; the paired comparison indicates a statistically significant within-person increase.	Supported
H2: Perceived ease of use (PEOU) is positively associated with perceived usefulness (PU).	Linear regression: PU predicted by PEOU	PEOU was positively and significantly associated with PU ($t = 4.29$; $p < 0.001$; $R^2 \approx 0.06$).	Supported
H3: Perceived usefulness (PU) positively predicts behavioral intention (BI) to use the AI-basket function.	Linear regression: BI predicted by PU	PU showed a strong positive and significant effect on BI ($b \approx 0.44$; $t \approx 10.69$; $p < 0.001$; $R^2 \approx 0.28$).	Supported
H4: Perceived ease of use (PEOU) is directly positively associated with behavioral intention (BI) to use the AI-basket function.	Linear regression: BI predicted by PEOU	The direct association between PEOU and BI was small and not significant ($b \approx -0.039$; $t \approx -0.78$; $p = 0.436$; $R^2 \approx 0.002$).	Not supported
H5: Higher objective AI performance is positively associated with perceived usefulness (PU).	Regression: PU_z predicted by Performance-Index_z; component model with log(E10)_z and log(T10)_z	The performance index was positive and significant ($b = 0.201$; $p = 0.006$). In the component model, editing effort was negative and significant, whereas processing time was not significant.	Supported
H6: Higher objective AI performance is positively associated with perceived ease of use (PEOU).	Regression: PEOU_z predicted by log(E10)_z and log(T10)_z	Editing effort was negatively and significantly associated with PEOU ($b = -0.136$; $p = 0.022$), whereas processing time was not significant; the overall model was marginal.	Partially supported
H7: Higher objective AI performance is positively associated with behavioral intention (BI).	Regression: BI_z predicted by log(E10)_z and log(T10)_z	The model was significant ($R^2 = 0.189$). Editing effort was a strong negative predictor of BI ($b = -0.446$; $p < 0.001$), whereas processing time was not significant.	Supported

Note: IU = increased online grocery usage intention; PEOU = perceived ease of use; PU = perceived usefulness; BI = behavioral intention; E10 = editing effort per ten products; T10 = processing time per ten products. Higher values of the performance index indicate better objective performance, i.e., lower time and editing effort. All analyses are based on $n = 297$ valid cases.

Overall, the summary confirms a clear pre–post increase in online grocery usage intention, support for the core TAM mechanism through perceived usefulness, and a consistent performance-related pattern in which editing effort is more relevant for acceptance than processing time.

To provide a consolidated visual summary of the performance-related hypotheses, Figure 4 reports the standardized coefficients of editing effort and processing time in the component-level models for PU, PEOU, and BI.

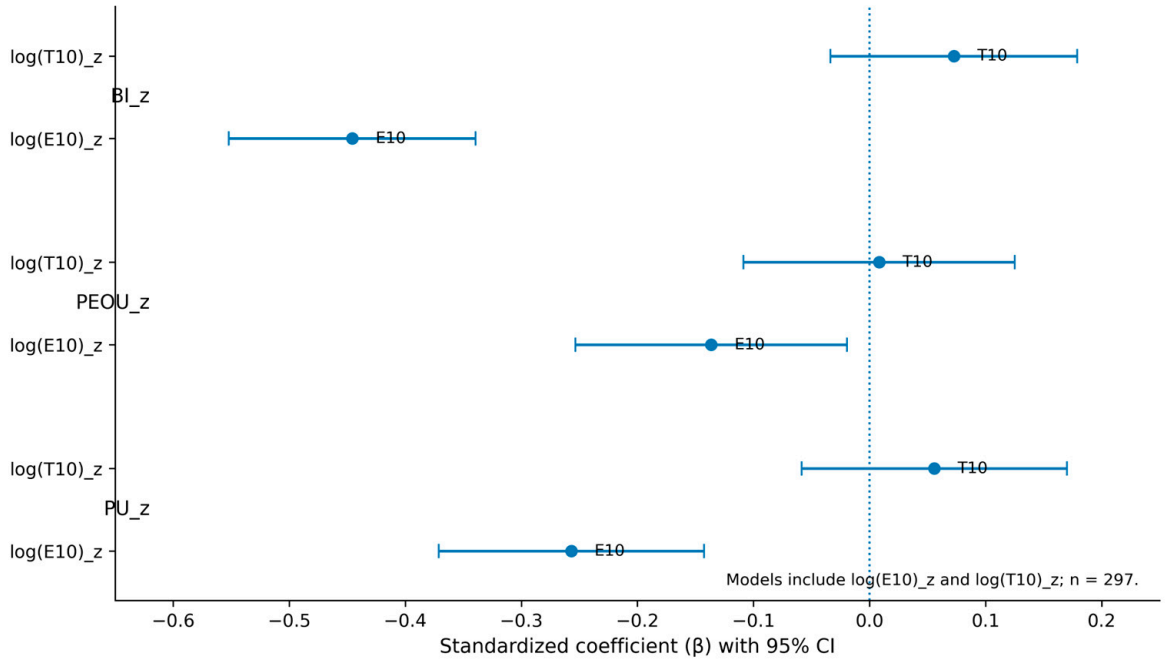


Figure 4. Standardized coefficients of objective performance indicators in the performance-related models.

5. Discussion

5.1. Overall Interpretation of the Findings

The aim of this study was to explain the acceptance of an AI-pre-filled basket in Austrian online grocery retailing and to link acceptance indicators to objective performance measures of the interaction. The central finding is a clearly identifiable acceptance-related intention shift: in the within-person pre–post comparison, online grocery usage intention was significantly higher after the AI-basket interaction than at baseline. This increase is not only statistically significant, but also substantial in descriptive terms, with mean scores rising by roughly 20 points on the 0–100 scale. Given the one-group pre–post design, this result should be interpreted as a short-term within-person intention shift following interaction with the AI basket, rather than as definitive causal evidence of market-level adoption effects.

Substantively, this pattern is particularly plausible in online grocery retailing because the main burden does not lie in a single product choice, but in a bundled decision across many items, with effort and cognitive load concentrated in basket construction and correction [7,9,18]. A pre-filled basket shifts the starting point from an "empty basket" to an "editable proposal," thereby potentially reducing search, selection, and planning effort. This logic aligns with choice-architecture mechanisms: default and starting-point settings can steer decisions toward a suggested option without formally restricting choice and have been documented as effective interventions in online basket/cart contexts [23]—including randomized evidence that pre-filled/default carts influence what consumers purchase and keep in the basket [19,20]. At the same time, the AI basket is not a rigid prescription but an editable proposal. The observed pre–post increase can therefore be read as a combination of (i) reduced initial friction and (ii) experience-based usefulness: participants experience directly that entry into the digital shopping process reaches a functional starting state more quickly, and that correcting an existing set can require less effort than building a complete basket from scratch in high-item-count grocery tasks [7,9].

The additional modeling of post-task online grocery usage intention supports this interpretation. The multivariate model shows that post intention is systematically associated

with acceptance constructs (especially BI and PU) and, simultaneously, with process-load indicators. Thus, the pre–post shift is not only visible as a mean difference, but embedded in a coherent explanatory structure: the observed pattern suggests adoption-relevant potential, and the level of post-task intention varies with subjective acceptance mechanisms as well as experienced interaction load.

5.2. Acceptance Mechanisms in TAM: Usefulness Dominates, Ease of Use Operates Primarily Indirectly (H2–H4)

Hypotheses H2–H4 test the core TAM logic in the specific application context of an "AI basket". Overall, the pattern of results closely matches the classical structure of the Technology Acceptance Model: PEOU is positively associated with PU (H2), and PU is a strong predictor of behavioral intention to use the AI function (H3) [16,24,25]. Importantly, this structure is consistent with meta-analytic evidence showing that (across many TAM applications) the PU → BI effect tends to be stronger than the PEOU → BI effect, with PEOU operating primarily through PU. In the present setting, this dominance of usefulness is substantively coherent: in AI-based shopping assistance, the primary focus is not the ease of use per se, but instrumental value (time/effort savings, faster attainment of an acceptable basket, reduced cognitive burden). Thus, the application context corroborates the TAM assumption that usage intention is mainly driven by usefulness judgments, while the ease of use primarily operates via perceived usefulness [16,24,25]. This is also compatible with prior online grocery acceptance work, in which perceived usefulness emerges as a key determinant of intention [1,17].

By contrast, H4 (a direct PEOU → BI effect) is not supported. This null finding is interpretively informative for AI baskets: it suggests that "effortless operation" functions as a necessary baseline expectation, but does not show an independent direct association with behavioral intention once usefulness (PU) is considered. Put differently, in the present setting, the ease of use is less an independent driver of intention and more an enabling condition that supports usefulness evaluations [25]. This point is central for the discussion because it specifies the acceptance levers: in the early diffusion phase of a basket-level AI function, usability optimization may reduce barriers, but intention formation is primarily carried by perceived added value.

5.3. Subjective Acceptance Versus Objective Performance: Evidence for a Perception–Performance Coupling with Clear Edit Dominance (H5–H7)

A key contribution of this study is the linkage of TAM constructs with objective performance/process measures. Conceptually, this addresses a well-known issue in recommender-system and AI-interface research: technical/system-centric quality and user-centric acceptance are related, but not identical, and should be evaluated with multiple complementary perspectives rather than "accuracy-only" views [27,33]. The present results indicate such a coupling in principle, but selectively and with a clear dominance of editing effort over pure processing time.

For PU (H5), objective performance is significant, albeit with a small explanatory contribution at the index level. The decomposition shows that the association is primarily driven by correction/rework demand (edits), not by duration. This supports a process-psychological interpretation: users infer usefulness less from "How long did it take?" and more from "How much did I have to correct because the proposal did not fit?". In this sense, editing effort operates as an immediately observable quality signal of output fit, aligning with user-centric perspectives that link experienced system value to objective interaction characteristics [26,33].

For PEOU (H6), an analogous picture emerges: editing effort is negatively linked to ease-of-use evaluations, while the time component does not provide an independent

contribution. This is plausible if PEOU is understood not only as interface usability, but as "effortless achievement of a correct outcome"—in other words, interaction quality and output quality converge when correction demand is salient [33].

The performance–intention linkage is most pronounced for BI (H7): objectively, more required edits are clearly associated with lower behavioral intention, while time again plays a secondary role. This concretizes the bridge from performance to adoption: not "speed" in the narrow sense, but "observable misfit expressed in the need for corrections" is the performance channel that translates into usage intentions. From an IS perspective, this is consistent with fit and success logics: when system output matches task requirements, rework decreases and the technology is more likely to be evaluated as beneficial and worth using [26,27].

5.4. Control, Editability, and Algorithmic Reactions as an Additional Explanatory Layer

The strong role of editing effort can also be contextualized using established findings on algorithmic reactions. Research on algorithm aversion shows that people may disproportionately devalue algorithmic support after perceived errors, even when algorithms perform well on average [28]. At the same time, willingness to use algorithms increases substantially when users can adjust outputs and thereby exert control—i.e., modifiability mitigates aversion [30], and autonomy-supporting designs can increase acceptance [15]. In parallel, the literature documents algorithm appreciation—contexts in which people even prefer algorithmic recommendations (e.g., under complexity and expected consistency) [29].

Applied to AI baskets, this implies a differentiated acceptance logic: editability is a necessary governance and autonomy condition so that a pre-filled basket is not experienced as a loss of control [15,30]. At the same time, the volume of edits itself constitutes an experienced error signal. High correction demand means not only "more work," but also "the AI does not understand my shopping," which can depress perceived usefulness and ultimately BI [28,30]. This also helps to explain why time is systematically less relevant: time can increase without the output being experienced as "wrong" (e.g., careful review), whereas edits represent immediate corrective action.

5.5. Transparency, Explainability, and Trust as Translation Mechanisms Between Performance and Acceptance

The selective coupling between objective performance and subjective acceptance suggests that translation mechanisms intervene between "system performance" and "user perception." In particular, transparency and explainability are frequently discussed as bridging variables: explanations can help users to interpret suggestions as comprehensible and context-appropriate, supporting trust calibration and acceptance rather than blind reliance [34], and experimental evidence shows that explanation scope/modality can shift understanding, trust, and attitudes toward recommender systems [35]. For AI baskets, this implies concrete cues such as "Why this product?", "replaced due to availability," or "fits your preferences," which may sustain perceived usefulness, even when not every item is perfect, —because they can raise error tolerance and frame decision-making as a cooperative process [34,35].

At the same time, transparency is not automatically beneficial. Experimental evidence shows that providing more insight into an AI system's internal process can, under certain conditions, reduce trust and even impair user performance—highlighting a "more transparency is not always better" caveat [36]. This ambivalence matters for interpreting the results: the observed H1 pattern can arise despite only moderate performance couplings if the function is experienced as a useful starting point; however, translating technical quality into stable PU/BI may depend on whether explanations are plausible, appropriately scoped, and cognitively aligned with the task [34–36].

In the online grocery context, trust and perceived risk (e.g., quality/freshness uncertainty, substitutions/stockouts, delivery reliability) are traditionally salient and can shape usage intentions; accordingly, acceptance judgments toward an AI function are unlikely to target the algorithm in isolation, but are embedded in platform and process trust [8]. Empirical adoption research in online grocery also emphasizes risk and trust dimensions alongside benefit/effort drivers as relevant determinants of intention [1,37]. Thus, trust-oriented design (including how the AI communicates substitutions or uncertainty) is a plausible lever for stabilizing acceptance beyond immediate task-effort gains.

5.6. Overall Picture and Contribution to the Discussion on AI Baskets in Online Grocery Retailing

Taken together, the findings yield a coherent acceptance narrative: (1) Interaction with an AI-pre-filled basket was associated with a substantial short-term increase in online grocery usage intention (H1), indicating that such a function may support adoption by reducing perceived process burden. (2) Intention formation toward the AI function follows the TAM core logic, with usefulness judgments clearly dominating and the ease of use operating primarily indirectly via PU (H2–H4) [16,24,25,38]. (3) The linkage to objective performance is present but asymmetric: the decisive performance channel is correction/rework demand (edits), whereas pure duration is less acceptance-relevant (H5–H7). This pattern aligns theoretically with fit, control, and user-centric evaluation perspectives [15,26,27,39] and supports the view that users evaluate AI assistance less by abstract model quality and more by experienced fit, autonomy, and the need for "rework" [28,30].

Accordingly, this study positions AI baskets as a specific, basket-level assistance function whose success does not depend solely on predictive capability, but on how performance translates into perceived usefulness within the process: from the user's perspective, a "good" basket is primarily one that generates little corrective work and is simultaneously framed as a controllable proposal.

6. Implications

6.1. Theoretical Implications

This study contributes to technology acceptance research in e-commerce by (i) testing the TAM core (PEOU, PU, BI) in the specific application context of an AI-pre-filled basket and (ii) linking the acceptance mechanism to objective process and performance indicators derived from log data. In doing so, TAM is not "replaced," but applied in a highly effort-driven shopping context (online grocery retailing) in a way that makes the translation of usage experience into behavior-proximal intention measures—and its embedding in observable interaction behavior—empirically tangible. In the TAM tradition, perceived usefulness and the perceived ease of use are central cognitive evaluation constructs that structure usage intention [16,24,25]; more broadly, meta-analytic evidence in online shopping research shows that TAM-consistent drivers (including convenience and technology-related beliefs) are among the core determinants of purchase intentions and behavior [40].

First, the findings support the TAM core logic in the form of a usefulness cascade: PEOU exhibits a robust positive association with PU, and PU, in turn, emerges as a substantial predictor of behavioral intention to use the AI function (BI) [16,24,25]. Thus, in the AI-basket setting, "usefulness" is confirmed as the key proximal, instrumental evaluation, whereas ease of use appears to operate primarily through perceived usefulness. This is theoretically relevant because usefulness is not interpretable here as an abstract technology preference, but as process relief in a multi-item task (creating/reviewing/adapting a shopping basket) [7,9].

Second, the absence of a significant direct PEOU → BI effect in the bivariate specification (H4) is theoretically informative in this application context. This suggests that "ease of use" does not dominate intention formation as an independent, directly intention-driving dimension, but becomes relevant primarily when it translates into an outcome- or process-related gain experienced as useful (mediation via PU). This pattern is consistent with TAM extensions in which the direct PEOU → BI path is context-sensitive and often weaker once usefulness is accounted for [25,38].

Third, this study extends the acceptance perspective beyond self-reports by incorporating objective process load—particularly editing effort—as an observable "cost anchor" in the explanation. Substantively, the result profile indicates that not all performance dimensions function as equally salient psychological signals. While pure processing time shows no independent explanatory contribution across several specifications, editing effort repeatedly emerges as a negative predictor and/or negative correlate of key acceptance indicators. This distinction is theoretically aligned with user-centric recommender evaluation perspectives that explicitly separate (a) objective system/interaction characteristics, (b) subjective user perceptions (e.g., usefulness, usability), and (c) downstream behavioral outcomes (e.g., intention, continued use) [33,39,41]. For future conceptualizations of "performance" in retail AI assistance, this implies that correction demand (rework) can be a more psychologically diagnostic performance dimension than duration.

Fourth, the coupling of objective quality and subjective acceptance implicitly addresses a well-known asymmetry in AI interaction research: users are sensitive to perceived errors, and acceptance stabilizes particularly when outputs remain adaptable and user control is preserved. This logic aligns with evidence on algorithm aversion, according to which algorithmic support may be disproportionately devalued after observed failures, whereas the option to modify outcomes increases willingness to use [28,30]. The AI basket is positioned precisely within this tension: it is interventionist as a default starting point [23], yet remains correctable through editing. Theoretically, it follows that the acceptance of an AI basket cannot be explained solely by average system quality, but is structured by collaboration mechanisms (control, correctability, error tolerance); objective edit load thereby becomes both a performance measure and a potential acceptance mechanism [15,30].

6.2. Practical Implications

For practice and implementation in (Austrian) online grocery retailing, the findings yield several immediately actionable implications.

First, the robust short-term increase in online grocery usage intention suggests that an AI-pre-filled basket can be conceptualized not merely as a "nice to have," but as a potentially adoption-supporting function. For retailers, AI baskets can serve as an onboarding and reactivation instrument because they address the channel's core hurdle: the initial effort of basket construction in a high-item, effort-intensive task [7,9]. From a choice-architecture perspective, deploying a pre-filled basket as a modifiable starting point is consistent with default and starting-point mechanisms [23] and with evidence that pre-filled/default online carts can shift what users keep or purchase [19,20]. Strategically, this is relevant because it may stimulate not only usage of the AI function, but potentially overall channel usage (as reflected in the acceptance criterion applied in this study).

Second, the performance-related results suggest that optimization should not be narrowly framed as "making it faster," but rather as "reducing rework." Practically, this implies that model and assortment quality should be managed to lower correction demand (fewer replace/remove/add loops). Accordingly, edit-based metrics (e.g., normalized edit intensity per basket size; adoption/hit stability metrics) are suitable operational KPIs because they capture the performance signal that appears most acceptance-relevant in the

observed relationships and map closely to user-centric recommender evaluation constructs linking interaction burden and perceived usefulness to intention outcomes [33,39,41]. In the operating model, this can be translated into continuous monitoring using controlled online experiments (A/B tests, ramp-ups, cohort comparisons): beyond conversion and order value, edit load can serve as an early indicator of perceived usefulness and usage intention [42].

Third, the combination of acceptance and aversion logic implies that interaction design should be treated as a key acceptance lever: the AI basket must remain experienceable as a "proposal with control." Concretely, this entails the following: (i) changes must be low-friction, reversible, and feasible without additional search costs (fast replacement/removal, strong substitute suggestions); (ii) AI interventions (substitutions, prioritizations) should be clearly identifiable; and (iii) users should retain autonomy to ignore suggestions or to control the degree of automation. These principles align with evidence that modifiability reduces algorithm aversion [30] and with validated human–AI interaction guidelines emphasizing control, feedback, and appropriate transparency over the interaction lifecycle [43].

Fourth, the communication of the function should be consistently usefulness-oriented. Because PU is the central intention-driving mechanism in the analyses, retailers should communicate benefits in process terms (planning relief, reduced search and correction effort, a faster "usable" starter basket) rather than relying on generic "AI" positioning [16,40].

Fifth, from a governance and UX perspective, pragmatic transparency should be planned. Even brief explanatory cues (e.g., "frequently purchased," "fits your preferences," "alternative due to availability") can help users to classify suggestions as plausible and thereby facilitate the translation of system output into perceived usefulness [34,35]. At the same time, transparency is not automatically beneficial; depending on how it is implemented, it can reduce trust or overwhelm users, so explanation scope and presentation should be calibrated to the task and context [34–36]. In online grocery specifically, trust and perceived risk (e.g., substitutions/stockouts, quality/freshness uncertainty) are salient; therefore, the acceptance of an AI basket is likely embedded in broader platform/process trust rather than directed at the algorithm alone [1,8,37].

In sum, the practical implications can be bundled into a set of priorities: (1) deploy the AI basket as an adoption-driving default intervention, (2) manage quality not only via time, but primarily via edit load, (3) design control/editability as the acceptance architecture, and (4) reinforce perceived usefulness and plausibility through transparent, process-proximal communication.

7. Limitations and Future Research

7.1. Limitations

(1) **One-group pre–post design and causality.**

This study relies on a field-proximate one-group pre–post design [44,45]. While this design is useful for exploratory evidence on the direction and magnitude of change, it does not allow for strong causal attribution in the sense of a controlled counterfactual [44,45]. Classic validity threats include history and maturation effects (contemporaneous influences during the measurement period), testing effects (the pre-measure influences the post-measure), instrumentation (changes in measurement conditions), and regression to the mean for extreme baseline values [44,45]. In addition, given the intervention-like setting, demand characteristics are plausible: participants may infer the study's hypotheses and adjust their responses accordingly [46,47]. These limitations affect not only H1 (change) but also the interpretation of why the change occurs.

(2) **Setting, task realism, and ecological validity.**

The setup is field-proximate (immediately before a real shopping trip) but standardized in relevant respects: completion on a laptop, a fixed shop/product catalog, and a clearly defined task ("edit the basket until satisfied"). This entails two constraints. First, transferability to natural usage situations (e.g., smartphone app use at home, under time pressure with interruptions) is not guaranteed; device and context differences may systematically affect the perceived ease of use and interaction patterns (edits/time) [48,49]. Second, the full end-to-end purchasing process is not observed (e.g., checkout, delivery fees, delivery slots, substitution rules, complaint/return experiences). In online grocery retailing, these process components can substantially shape channel choice; consequently, it remains unclear to what extent the measured acceptance reaction would persist once financial and logistical consequences are directly experienced [1,8].

(3) **Sample characteristics and generalizability.**

Intercept recruitment in multiple cities increases practical relevance but may introduce selection mechanisms: (i) individuals willing to participate in an experiment immediately before shopping may differ in technology openness, time budget, or involvement; (ii) the sample does not necessarily represent the population of existing heavy users of online grocery; and (iii) the Austrian context (market structure, delivery coverage, online grocery maturity) limits international generalizability. Thus, external validity is plausible but not automatic—particularly for markets operating under different delivery and pricing regimes [50].

(4) **Measurement: slider scales, short-term intentions, and novelty.**

Using 0–100 sliders (VAS/slider formats) enables fine-grained judgments but can also introduce measurement artifacts, including higher variance, anchoring/rounding effects, and the device-dependent usability of the scale [51–53]. In addition, the two-item IU scales showed acceptable but not identical internal consistencies across the pre- and post-task measurements; this may reflect the more abstract reference point of the pre-task assessment compared with the more concrete, experience-based post-task assessment. Therefore, the pre–post increase should be interpreted as a robust short-term intention shift, while the exact magnitude of the change should be interpreted with appropriate caution. Moreover, acceptance constructs are measured as intentions immediately after a one-time usage experience, which implies a classic limitation for behavioral prediction. Meta-analytic evidence suggests that intentions explain behavior, but a systematic intention–behavior gap remains—especially for repeated, everyday behavior [54,55]. Closely related, a novelty effect is possible: first-time AI interaction may trigger short-term positive evaluations (interest, "wow" effect, perceived innovativeness) that may attenuate with routinization or—following repeated error experiences—potentially reverse [56,57].

(5) **Objective performance indicators: interpretive latitude of log data.**

Time and edit measures are behavior-proximal indicators, yet they are not "pure" system quality: (i) they also reflect user strategies (perfectionism, brand loyalty, planning style), task heterogeneity (household complexity), and situational constraints; (ii) they capture interaction costs but only indirectly reflect the substantive quality of the final basket (e.g., fit to preferences, dietary restrictions, price/promotion sensitivity, freshness preferences); and (iii) they are sensitive to the shop's UI design and search/filter functionality. Accordingly, high edit effort can indicate both "weak AI" and "high individualization/high aspiration levels." This is central for performance-theoretical interpretation and suggests that future work should operationalize performance multi-metrically (not only "effort," but also "outcome quality") [33,39,41].

(6) **Model logic and potential endogeneity.**

The regression models are appropriate for hypothesis testing in the TAM tradition, but remain observational in nature: perceptions (PU/PEOU) and intention (BI) are measured at the same post time point, so reciprocal influences and common causes (e.g., general technology affinity, trust, risk aversion) cannot be ruled out [58]. For the performance-related hypotheses, an additional concern applies: performance may shape perceptions, but perceptions may also influence editing behavior (and thus edits/time). Such endogeneity is plausible in AI interactions (e.g., low trust → more intensive checking/edits → apparently "worse" performance values), which limits interpretability regarding the direction of some coefficients [59].

7.2. Future Research

(1) **Stronger causal inference via RCTs/A–B tests in the live shop environment.**

The most direct next step is a randomized field experiment (A/B test) in a real online shop: AI-basket function "on" vs. "off" (or graded variants: default basket, partial basket, suggestions only) [42,45]. This would enable the measurement of actual behavioral outcomes (conversion, basket size, repeat purchase, checkout abandonment) and provide substantially stronger causal identification than a one-group pre–post design [45]. Complementary designs include cross-over setups (same users under alternating conditions) or cluster randomization (e.g., by region/delivery slot) to test contextual dependencies systematically [60–62]. Methodologically, primary endpoints should be pre-registered (e.g., repeat purchase rate after 4–8 weeks) [60].

(2) **Longitudinal designs and the intention–behavior translation.**

A key extension is to test stability: does the increased intention persist once the novelty effect fades, and does it translate into repeated use [56,57]? Longitudinal designs (panels; log data across multiple purchase cycles) could examine whether PU/PEOU/BI consolidate or polarize after 3–5 usage episodes. This directly addresses the intention–behavior gap and allows acceptance to be modeled as adoption over time [54,55].

(3) **Segmentation and moderation: who benefits, and under which conditions?**

Future research should treat heterogeneity not only as a control strategy but as theory testing. Relevant segments include heavy vs. light users of online grocery retailing, household complexity (e.g., children, dietary restrictions), price/promotion sensitivity, and spatial context variables (delivery coverage, delivery-slot availability). Methodologically, interaction models or hierarchical models (users nested in regions/shops) are suitable to represent contextual moderation more rigorously [63]. The goal is a differentiated answer as to whether AI baskets primarily reduce entry barriers (adoption among new users) or primarily increase efficiency for existing users (retention/convenience).

(4) **Extended performance metrics and user-centered evaluation.**

The "edits/time" logic should be complemented with outcome-proximal quality metrics: adoption rate, hit rate, substitution quality, basket alignment with intended needs (e.g., via eliciting an "intended list"), price/budget fit, and—where feasible—post-delivery satisfaction. It is well established in recommender-system research that pure "accuracy" or system-centric metrics explain the user experience only incompletely; evaluation should therefore be multi-method and user-centered (e.g., perceived fit, transparency, control, and trust as bridging variables) [33,39,41].

(5) **Mediation and collaboration logic: performance → perception → intention.**

Substantively, an explicit mediation test is a natural next step: objective performance affects PU/PEOU (or perceived fit), which in turn drives BI (and potentially actual usage). [64]. Such models could integrate moderators that are particularly relevant in AI interactions, including perceived control (editability), transparency/explainability, and trust [34,36]. Research on algorithmic reactions, for example, shows that users penalize algorithms strongly after errors, while acceptance increases when adjustment/override is possible—precisely the mechanism that is theoretically central for editable baskets [28,30].

(6) **Replication across devices, retailers, and countries.**

Finally, systematic replications are needed: (i) mobile-first use (app) vs. desktop/laptop, (ii) multiple retailers with different search/sorting logics and substitution rules, and (iii) cross-country comparisons with differing levels of online grocery maturity. This would clarify whether observed patterns (e.g., the dominance of edit effort over time) are robust or highly contingent on UI and process rules [49].

Overall, the findings suggest that AI-pre-filled baskets should be understood not merely as technical recommendation tools, but as consumer-facing decision-support systems whose acceptance depends on perceived usefulness, controllability, and low correction demand. The central practical message is therefore clear: AI grocery baskets should be designed as controllable, editable, low-rework systems rather than as speed-oriented automation tools.

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Institutional Review Board Statement: The manuscript reports research involving human participants, as it includes a survey/experimental study. This study is a social and economic science study involving adult participants. No medical examinations or health-related interventions are carried out, and no sensitive medical data are collected. No vulnerable groups of persons are specifically included. The study involves minimal risk. The level of burden associated with participation corresponds to everyday use of an online shop and the completion of short questionnaires. Therefore, ethical approval was not required for this study. According to BOKU University, this is to confirm that at BOKU University it is not mandatory to submit research proposals to the Ethics Committee and thus have an ethics approval before data is collected. The Statutes of BOKU University (section C1. § 13c. (1)) state that researchers can submit a research proposal to the Ethics Committee. This submission needs to be justified, e.g. because the funder of the research or the journal in which the results are to be published requires it. At BOKU University, submitting a proposal to the Ethics Committee is thus a voluntary procedure which needs to be completed before data collection begins.

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