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Abstract:

Design for reflection in human-computer interaction (HCI) has evolved from focusing on an abstract and outcome-driven design subject towards exposing procedural or structural reflection characteristics. Although HCI research has recognized that an individual's reflection is a long-lasting, multi-layered process that can be supported by meaningful design, researchers have made few efforts to derive insights from a theoretical perspective about appropriate translation into end-user visual means. Therefore, we synthesize theoretical knowledge from reflective practice and learning and argue for a differentiation between time contexts of reflection that design needs to address differently. In an interdisciplinary design-science-research project in the mHealth nutrition promotion context, we developed theory-driven guidelines for “reflection-in-action” and “reflection-on-action”. Our final design guidelines emerged from prior demonstrations and a final utility evaluation with mockup artifacts in a laboratory experiment with 64 users. Our iterative design and the resulting design guidelines offer assistance for addressing reflection design by answering reflective practice’s respective contextual requirements. Based on our user study, we show that reflection in terms of “reflection-in-action” benefits from offering actionable choice criteria in an instant timeframe, while “reflection-on-action” profits from the structured classification of behavior-related criteria from a longer, still memorable timeframe.

Keywords: Reflection, Reflection-based Design, Reflective Practice, Reflective Learning, Reflection-in-action, Reflection-on-Action, Design Guidelines, Design Science Research, Behavior Change.

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Introduction

Advances in the nature and design of mobile technology and its interfaces offer multiple ways to collect and monitor personal data for self-reflection to gain personal insights, deeper self-understanding, or self-regulation skills. Users track and reflect on their personal data for different purposes, such as finance, productivity, learning, or health behavior (Epstein et al., 2020). Unhealthy lifestyles, such as following an unhealthy diet throughout longer lifespans or even a lifetime, lead to obesity and chronic illnesses that threaten individuals' lives (WHO, 2014). The World Health Organization (WHO, 2021) accounts for 71 percent of global deaths to noncommunicable diseases (NCDs) (e.g., cardiovascular diseases, cancer, and type 2 diabetes) and are highly associated with undesired behaviors such as regular intake of unhealthy foods. A common way to address this problem involves helping people reflect on their own behaviors via designing mobile health (mHealth) applications and analyzed personal data displays to support healthier behaviors.

More generally, design for reflection in HCI integrates approaches from multiple research streams such as interactive systems, personal informatics and computing, and persuasive or theory-driven design for behavior change support systems. Design efforts have evolved from adopting an outcome-based perspective to measure reflection success based on specific outcomes (e.g., a specific skill, a learning outcome, and/or behavior change) to more holistically understanding reflection as an individual or shared contextual process (Baumer, 2015; Feustel et al., 2018; Kocielnik et al., 2018; Murnane et al., 2018). Since the HCI design literature does not define reflection in any unique way, we borrow Schön's definition of the term (1983). Here, reflection constitutes a critical thinking process and the ability for professional and lifelong learning, which he calls "reflective practice". Schön (1983) distinguishes reflection contexts based on whether they reflect current situations (i.e., actions called "reflection-in-action" (RIA)) and or past actions (i.e., "reflection-on-action" (ROA)). However, existing approaches to design for reflection assume that reflection naturally occurs after data analysis is displayed without considering different reflection contexts (Slovák et al., 2017). Mobile health (mHealth) approaches, such as behavior change systems, do not offer structural reflection support (Kocielnik et al., 2018). Current mHealth approaches, such as promoting healthy eating, are more aligned with classical behavioral theories from cognitive psychology. Researchers have commonly assessed their success through distinct health outcomes such as intake- and body-related measures that range from calorie intake to personal weight, and blood values.

The challenge for designing for reflection in personal user interfaces involves supporting individual reflection as a long-lasting process with respective technology means and contexts. Because individuals use mobile displays fleetingly and due to reflection's complex nature, one cannot easily provide accompanied support for the whole reflection process. HCI requires solutions that enrich deeper "in-moment" reflection to achieve deeper insights, understanding, or even behavior change. Still, the understanding and available knowledge in HCI to meaningfully scaffold reflection for design remain fuzzy or too abstract. It does not more deeply consider reflection through a theoretical grounding and describe concrete reflection purposes or contexts (Baumer, 2015). Although current design frameworks and approaches integrate or synthesize knowledge from reflection theory (Baumer, 2015; Fleck & Fitzpatrick, 2010; Slovák et al., 2017), we lack beneficial ways to leverage personal data analysis through visual user interfaces for individual reflection. Current approaches often fail to guide users into reflective practice. Therefore, we see a need to identify useful reflection contexts that, in combination with designing appropriate technological systems, bear meaningful reflection that allow people to achieve personal insights and understanding in the present or future.

Given that the literature lacks concrete design knowledge for meaningful reflection contexts that personal visual user interfaces provide, we offer design guidelines rooted in reflective practice from Schön (1983). We separate reflective practice into two different reflection contexts based on their timings, such as reflecting ongoing activities through RIA and reflecting past activities by ROA. This view on reflection from theory allows one to adopt a more detailed design perspective and, thus, consider reflection and structural assistance in developing and evaluating reflection design at a more granular level. We highlight RIA and ROA as encompassing structures to provide design knowledge that enables a more detailed description of the user's reflection process. We develop the design guidelines in an iterative design science approach based on Peffers et al. (2007). In particular, we consider a context that involves designing mHealth interfaces for reflection support to promote individuals' dietary decisions for healthier outcomes since maintaining healthy nutrition involves much complexity. Further, we align our work with the following research questions:

RQ1: How can we develop a reflective practice using RIA and ROA in personal user interfaces for mHealth?

RQ2: Can the proposed reflection design help users understand personal data to provide actionable knowledge in terms of RIA and behavioral pattern analysis in terms of ROA?

With this work, we contribute design guidelines and visual design patterns for RIA and ROA to support reflective practice with the help of mHealth data displays to promote healthy nutrition.

We structure this paper as follows: in Section 2, we consider existing and relevant questions in the field and identify the need for additional research in reflection design related to HCI. We use reflective practice's core elements (Schön, 1983) and theories-of-action (Argyris & Schön, 1997) to introduce the theoretical background. We also describe related work for reflection design in the HCI field and the mHealth context. In Section 3, we describe the overall design science research approach we conducted to develop, demonstrate, and evaluate our design artifacts in the mHealth promotion for nutrition context. In Section 4, we present our design guidelines based on the theoretical foundation of reflective practice and their implementation in prototypes through visual design patterns. In Section 5, we offer the results from our final evaluation with our artifacts in a laboratory experiment and provide an overview of the final design guidelines. In Section 6, we relate our findings to existing research, discuss their theoretical and practical contribution, and present the study's limitations.

1 Background

1.1 Reflective Practice and Learning

Schön (1983) has significantly influenced discussions on reflection and its role in education and learning in professional practice. In his understanding, reflection constitutes a critical thinking process and the ability to learn professionally throughout one's life, which he refers to as "reflective practice". In this context, Schön (1983) separates reflective practice based on timing: reflection-in-action (RIA) and reflection-on-action (ROA). RIA refers to the reflection process or thinking about an ongoing action and relates to individuals' problem-solving capabilities to optimize an ongoing action in an intuitive non-interruptive way. RIA focuses on optimizing how well one performs current and repeated practice through tacit professional knowledge. ROA, on the other hand, underpins the reflective process after an activity by thinking critically about past behaviors in terms of underlying values, ethics, or policy. ROA aims at achieving a meta-perspective on strategies used by re-thinking or even changing the underlying individual, public or ethical values. In later work, Argyris and Schön (1997) described factors that influence human actions that either support or inhibit reflection and, therefore, affect individual and organizational learning. They differentiated human actions into "single-loop learning" and "double-loop learning". In essence, the former, which error detection or mismatched goals trigger, constitutes a problem-solving approach to optimizing a distinct outcome based on internalized knowledge. Argyris and Schön (1997) refer to a process by which one thinks or learns using externalized knowledge from single-loop learning as higher-level critical thinking. It involves critically inspecting the individual perspective via reflecting on meta-values such as a chosen goal's appropriateness and efficacy in solving problems (Figure 1).

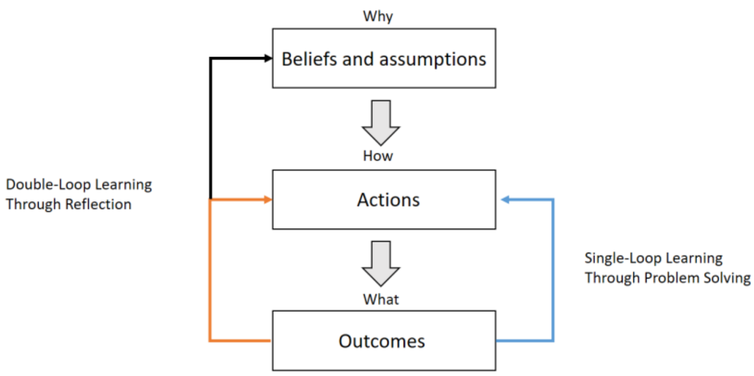

Figure 1. Single- and Double-loop Learning

Argyris and Schön (1997) highlight the relationship between information feedback and mental models as the basis for individuals' decisions based on previously trialing a solution in the real world. As Argyris and Schön (1997) do not distinctly define feedback, in this work, we rely on feedback as information that an agent provides about aspects of one's performance or understanding (Hattie & Timperley, 2007) from an educational learning perspective. Argyris and Schön (1997) argue that learning (through feedback from a valid informational source) constitutes an essential prior step to making (complex and poorly structured in particular) decisions. They support double-loop learning as the preferred learning form over single-loop learning and assign a specific role to (organizational) leaders as actors who own the required meta-knowledge for valid information to emerge in uncertain contexts. According to Greenwood (1998), reflective practice (in a healthcare context) functions merely as double-loop learning as redesigning a problem's structure (environment) correlates with performing an action itself.

1.2 Designing for Reflection in HCI

Reflection as an investigation object for design has become an increasingly investigated topic in HCI in the last decade (Baumer et al., 2014; Fleck & Fitzpatrick, 2010). Designing for reflection emerges from various research areas such as ubiquitous computing, personal informatics, and other HCI-related fields that design or social and behavioral sciences influence. The understanding of reflection in HCI research has shifted from focusing on outcomes to looking at structural or contextual elements of the reflection process for deeper, meaningful, or even transformative reflection experiences, including behavior change.

Li et al. (2010) first introduced reflection as an element that involves preparation, collection, integration, reflection, and action stages in their personal informatics systems model. Their model does not further characterize reflection even though it posits reflection as a required transcendent stage to action. Because HCI research has not clearly defined reflection and related concepts, Fleck and Fitzpatrick (2010) provided a synthesizing framework on the original reflection literature and approaches from HCI as guidance for how technology can support reflection that they split into different abstract reflection levels. They understand these levels—revisiting, revisiting with explanation, exploring relationships, and fundamental change—as building on each other, and they offer a means to address reflection by design that uses different technologies. By introducing "reflective informatics", Baumer (2015) offered a broader theory-driven understanding and shared reflection vocabulary by identifying the three dimensions breakdown, inquiry, and transformation. As a conceptual approach, reflective informatics offers a shared language on reflection and encourages a perspective in which one designs for and evaluates reflection through various technology interventions rather than one technology or system as a unique solution. Slovák et al. (2017) argued that designers need to carefully scaffold reflection in learners' experiences rather than simply triggering reflection from data. The authors draw on Schön's practical approach "design as reflection-in-action" (Schön, 1984) and apply the concept to identify factors that support transformative reflection. Their framework offers guidelines for designing emotional-learning environments that highlight explicit, social, and personal practicum components to transform users' thoughts, actions, or behavior.

Kersten-van Dijk et al. (2017) found evidence to support the potential for self-monitoring data and feedback via personal data displays to help people change their behavior. In particular, they found that self-insight that people gain via reflection through personal self-monitoring data and feedback plays a critical role in different phases of the transtheoretical model of behavior change (Prochaska & Velicer, 1997). Ploderer et al. (2014) emphasize the need for and challenges in designing system components for engagement and effective behavior change. They state challenges in designing reflective approaches such as RIA to appropriately communicate "knowledge in action" and find meaningful ways to present data for ROA. Lately, Ghajargar and Wiberg (2018) provided a different perspective on reflection design in HCI concerning behavior change. They distinguished between outcome-focused and process-focused reflection approaches and suggested that one should include artifact evaluations when designing interactive artifacts reflecting and "designing more thoughtfully" to tackle problems in focus areas such as sustainability and health.

To help people reflect more deeply via design and technology use, existing approaches to designing for reflection consider different aspects related to reflection. Inquiry elements include visually representing personal data in different formats (Choe et al., 2015; Cuttone et al., 2014; Prioleau et al., 2020), including social contexts (Bussone et al., 2019; Ploderer et al., 2014) or incorporating dialogic reflection methods in an agent to discuss personal visualizations (Kocielnik et al., 2018).

Knowledge for designing reflective systems remains fuzzy as approaches often lack a deeper grounding in reflection theory or models to help researchers and designers more deeply understand the process, supporting factors, and contextual requirements (Baumer, 2015; Baumer et al., 2014; Kersten-van Dijk et al., 2017).

1.3 Fostering Reflection in mHealth Applications

Data visualization fosters insights based on visual data or information representations (Ware, 2019). Visualizing health data and insight generation has increasingly gained importance due to recent technological developments and the health status of the population. Various purposes for generating, collecting, and analyzing data that emerge from the quantified-self movement (Quantified Self, 2021) and trends in mHealth and personal informatics have influenced how one can visually communicate health information. mHealth refers to using "mobile communications for health information and services…to improve health outcomes" (Nacinovich, 2011). From a personal informatics perspective, collecting and reflecting on appropriately analyzed behavioral data helps users to gain self-insights and motivates them to track and monitor their behavior (Li et al., 2010). Delivered by digital technology, visualized self-monitored data in combination with feedback can better disrupt undesired behaviors compared to tactile and auditory feedback (Hermsen et al., 2016).

Mhealth and personal informatics focus on visualization methods that offer reflection and motivation to help people use displays provided and track behavior more sustainably. The visualization techniques essentially result from the underlying data types' characteristics and can be distinguished into short-term or long-term data analyses. Cuttone et al. (2014) offer general visualization heuristics to support reflection that considers different timely interactions with users and their data in short- or long-term contexts, such as glancing overviews that allow for quick interpretation, representation formats for facilitating pattern or trend analyses, and effective ways to interact with visualizations (filtering, navigation, annotation, history). Short-term data analyses in mobile displays, such as glancing overviews on pre-defined key metrics or instant feedback that indicates performance gaps between current and desired behavior from a goal, provide a form of RIA for the moment users view them. Gouveia et al. (2016) identified glanceable feedback in physical activity trackers as having six design characteristics "abstract, integrating with existing activities, supporting comparisons to targets and norms, being actionable, having the capacity to lead to checking habits and to act as a proxy to further engagement" (p. 144). Popular examples for mHealth in nutrition use glancing overviews that frequently include daily burned and left calories and statistically distributed macronutrients retrieved from tracking input and physical activity levels. The manner in which food-logging applications understand and explain data visualizations represents an essential element in their design (Cox et al., 2017). However, we require further research on what data content and visual analyses help people reflect and achieve goals beyond simple weight loss (e.g., achieve a balanced healthy diet for pregnant women (Wenger et al., 2014) or diabetics (Desai et al., 2018).

Long-term analyses involve ROA and examine past data on health-related actions to support self-regulation and -management. Examples include retrospective data analyses on physical activity, sleep, heart rates, weight, and blood pressure (Colley et al., 2016) or factors related to medication adherence in chronic disease support (Backonja et al., 2018). Retrospective data analyses about individual nutrition other than calories relate to patient-generated data such as diabetes self-monitoring data (Feller et al., 2018).

While reflection in mHealth or personal informatics that visual self-monitoring data and analyses offer focuses on motivational gaps in users, general health data visualization focuses on techniques to narrow the communication gaps between poorly and highly literate users (Ancker et al., 2006; Arcia et al., 2013). Despite the trend to use statistical graphs and number representations for visual communication, visual cues (e.g., pictures or pictograms) as action directives show promises in communicating health messages, such as in low-literate populations (Garcia-Retamero & Cokely, 2013, 2017; Peregrin, 2010). In their work, Garcia-Retamero and Cokely (2013), Garcia-Retamero and Cokely (2017), and Peregrin (2010) highlight the potential for appropriately designed visual aids to communicate health-related information, specifically for people with low literacies (health risk, numbers, or graphs). Inappropriately analyzed and presented data that results in improper feedback often aggravates the process that users go through to make decisions before taking action (Rabbi et al., 2015). Challenges remain in providing appropriate data content and visualizations to generate relevant insights, health awareness, and risk perceptions that imply further action as part of longer-term health behavior change.

Therefore, in our work, we focus on providing design knowledge on reflection support that uses technology and, more specifically, comprehensive and actionable visual data analysis. In addition, we focus on improving an individual's dietary practices via mHealth tracking interfaces.

2 Method

We focus on separating reflection contexts in design with help from an iterative and theoretically driven design process in which we use core elements from reflective practice and learning as a relevant and rigorous design approach. Our research follows the design science research (DSR) methodology based on Peffers et al. (2007). This methodology allows one to develop design guidelines and system artifacts. System artifacts are instantiations of the design guidelines developed that we use to demonstrate and evaluate their practical utility. Following this methodology, we implemented the following phases in our research: 1) problem identification and motivation, 2) solution objectives, 3) design and development,

4) demonstration, 5) evaluation, and 6) communication. Figure 2 summarizes our approach along with these six phases.

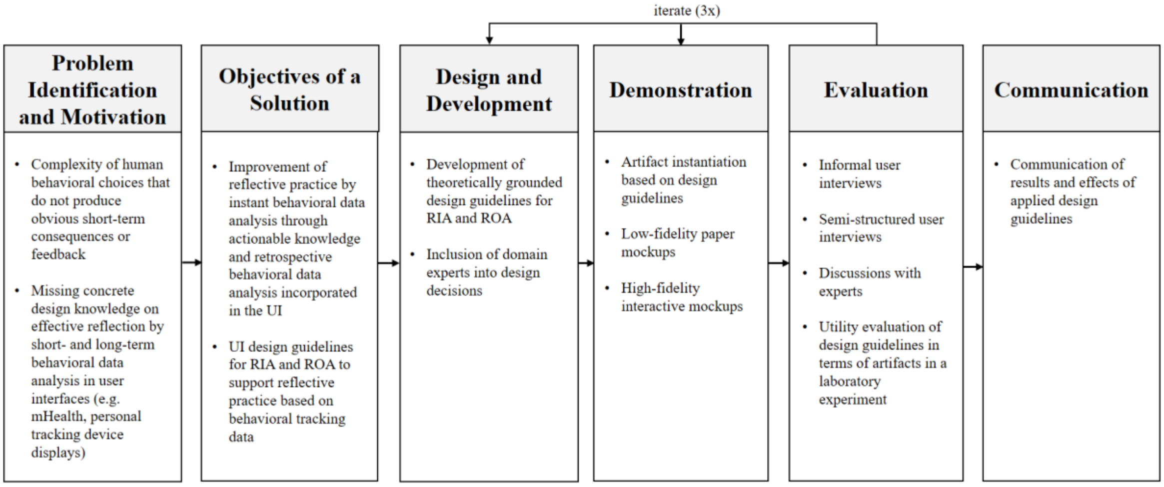

Figure 2. Instantiation of our Design Science Research Methodology along with the phases of Peffers et al. (2007)

First, we identified the following problems: 1) the complexity of human (dietary) behavior and related choices that do not result in obvious or early feedback and consequences, 2) missing concrete knowledge on how to provide reflection contexts via visual interfaces, and, thus, help users effectively understand short- and longer-term behavioral data analyses (see Section 2.2). Therefore, we identified a need to examine whether reflection design using visual cues (i.e., colored behavioral feedback) from experts on individual tracking data can improve health-related outcomes from using mHealth nutrition.

We then formulated our solution objective to inform efforts to reflectively design data-tracking interfaces that effectively analyze users' short-term and long-term behavioral data (see Section 2.3). In the design phase, we first developed theoretically grounded design guidelines to leverage reflective practices in mobile apps (see Section 4). Therefore, we further combined theoretical knowledge from reflective practice and learning with practical knowledge from literature in the HCI context to develop potential solutions (i.e., interface artifacts) to the problem.

In the first demonstration phase, we used our proposed guidelines to translate them into mobile user interfaces for monitoring, reflection, and promotion of a healthy diet. To do so, we first created low-fidelity paper mockups for RIA and ROA to test which representational design provides a solution to our problem. For RIA, we considered timely dietary choices by short-term nutritional tracking data in standard representational designs. The design comprised several nutrients that indicated the current intake state via color and the desired intake action via an external arrow cue. For the representational design, we initially used a speedometer, common in driving or energy-saving contexts, and a circular bar chart (donut bar chart). To demonstrate a potential solution for ROA, we created paper mockups on temporal nutritional intake values from tracking, which a graph that highlighted the nutrient saturation levels in its background displayed. In the second demonstration stage, we created different representational designs for RIA as part of low-fidelity paper mockups. Both representations used arrows as cueing information, whereas they differed in how they represented nutritional state information such as self-designed infographics and horizontal bar charts. In a third demonstration stage, we offered our final artifacts (see Figures 4 and 6) as high-fidelity mockups that we created in Adobe XD (release version 14.0.42).

In the evaluation phase, we iteratively assessed our artifacts to determine their quality and effectiveness. Based on the evaluations that resulted from the different artifact demonstrations, we could collect useful knowledge on how users generally perceived different representational styles and their usability. In the first iteration, we tested our elementary representational designs for usability and usefulness in 25 informal interviews in the field with university students and high school pupils at the Demo Day of the Faculty of Computer Science at the Technical University of Munich. The results indicated complexities in the design and the potential for information overload. In a second cycle, we evaluated the refined designs in 33 semi-structured interviews to identify the preferred representational design and to solve final usability issues. Additionally, we conducted six workshops with two experts from nutrition science for domain-specific knowledge and four experts from computer science for general usability aspects. Based on discussing the evaluation results, we made our design decisions. The results from evaluating our artifacts in the demonstration phase informed how we designed our final artifact for RIA and ROA, which we finally evaluated in a laboratory experiment (see Section 5) to our theoretically grounded design guidelines' utility. The results from the experiment informed how we formulated the final design guidelines that we present in this paper (see Section 4.1).

3 Design for Reflective Practice

We focused on developing design guidelines for reflection to promote a healthier dietary practice through RIA and ROA. In line with reflective practice and theories-of-action (Argyris & Schön, 1997; Schön, 1983), we argue that critically understanding previous behavior, supported by offering valid information, facilitates the reflective practice processes in users. We emphasize the supporting role that external information feedback from a valid knowledge entity plays in helping one critically understand individual (learning) actions, which subsequently creates a base for double-loop learning. Structuring the process along the temporal reflection contexts RIA and ROA serves as the basis of our design approach to more deeply understand the impact on user decisions through the visual interface design of these two reflection contexts. In this section, we introduce our theory-driven guidelines for RIA (see Table 1) and ROA (see Table 2) and the iteratively developed final artifacts designs (see Figures 4 and 6), which include visual design patterns (see Figures 3 and 5) and additional knowledge from demonstrations with users.

3.1 Design Guidelines for Reflective Practice (Artifact 1)

3.1.1 Design Guidelines for RIA

We rely on how Schön (1983) understands reflective practice, which emphasizes that one needs to make the "right" experiences to optimize an individual practice or learning. He specifically highlighted the role that a teacher or supervisor plays in creating appropriate task environments to help novices gain appropriate missing knowledge. If a learner does not have the experience to solve a professional, complex, or puzzling problem (also referred to as knowledge-in-action), Schön (1983) emphasizes that a professional teacher can reframe a problem's structure to help novices externalize tacit or missing domain knowledge. Schön (1983) interprets RIA as "a reflective conversation with the materials of a situation" that depends on a problem's or situation's contextual factors. Reflecting on these contexts or problem factors can help individuals interpret or reframe a problem differently and, thus, achieve a solution.

Referring to an individual's diet, dietary choices involve much complexity by nature (Sobal & Bisogni, 2009) and depend highly on the context since different interrelated internal and external contextual factors (e.g., food itself, the individual, and factors such as time, place, social context, and culture) influence them (Köster, 2009). These factors can further become a problem or a difficult task for individuals when they need to consider relevant criteria other than taste and preference. One important factor for informed choices in health concerns how individuals perceive specific health risks (Garcia-Retamero & Cokely, 2017). Additional missing nutrition or health knowledge and abilities to access and understand health-related information due to low literacy levels complicate or hinder well-informed choices. Expert knowledge in the nutrition domain indicates that healthy individuals require a balance of macronutrients (e.g., carbohydrates, protein, and fats) and micronutrients (e.g., vitamins, minerals, and amino acids) (Bailey et al., 2015). Available nutritional information (e.g., nutrition labels) in the environment can help individuals make healthier food choices (purchases). However, this knowledge normally remains tacit or unobvious with unpackaged foods if people do not possess additional domain knowledge.

Existing approaches for promoting healthy nutrition often follow generic concepts and do not reach people at an individual level (Celis-Morales et al., 2015). Many nutrition-related apps pay particular attention to weight loss via tracking calories in general and monitoring macronutrient distributions and, therefore, tend to give limited nutritional advice to individuals (Franco et al., 2016). Therefore, we consider the context around the dietary choices that an individual makes as involving: 1) food choice criteria (food context), 2) the nutrition knowledge the individual lacks, and 3) time. Thus, we propose the following design guideline for reflection-in-action (DG RIA):

> **DG RIA 1:** Provide a timely information context to help individuals make food choices by offering critical/important food choice criteria based on an individual's past behavior and external expertise.

A timely problem context enables one to reframe a problem, which Schön (1983) argues requires multiple steps as "a local experiment which contributes to the global experiment of reframing the problem." (p. 94). Testing several possible solutions as single local experiments can provide additional insights to view a problem from another viewpoint and, thus, serve as input on the path to finding a solution. A supervisor in this process can provide another (educational) perspective on the problem (factors), which can help an individual generate new knowledge to solve the problem. Specifically, valid information and feedback from an additional knowledge source can support learning processes (Argyris & Schön, 1997). Schön (1983) interprets specifically positive experiences as remembering functions that relate situations to action. While the human brain has a higher chance to store positive experiences than negative ones, unexpected or negative experiences can trigger reflective reasoning. In learning literature, positive feedback relates to increasing performance and motivation (Hattie & Timperley, 2007), whereas negative feedback helps one think critically about oneself and, thus, assess the causal criteria for one's failing (Sargeant et al., 2010). External feedback on task validity can help users to self-regulate their behavior as they better understand the problem factors that lead to observed outcomes (Balzer et al., 1989; Butler & Winne, 1995). The feedback offered in a learning environment should be communicated clearly, unequivocally, and at an appropriate time (Faulkner, 2000).

Habitual behavior that does not lead to early consequences often drives an individual's diet and, thus, remains unjudged. As long as the diet does not induce an obvious problem such as obvious weight gain or nutrient deficiencies that lead to perceivable health restrictions, individuals will likely remain with old habits and not reframe or judge their behavior. Breaking habits or learning new healthier dietary behaviors remains difficult due to the contextual cues and responses that individuals learn over their lifetime and lacking health awareness. Additionally, individuals lack professional knowledge to judge or assess their dietary behavior from an appropriate health perspective. Research in nutrition education and health behavior change has indicated that computer-tailored or personalized feedback could potentially benefit health behavior compared to purely information-based nutrition promotion campaigns (Brug, 1999; DiClemente et al., 2001; Hermsen et al., 2016). Automated instant performance feedback delivered in mHealth apps substitutes missing evaluation between counseling appointments (Chen et al., 2018). In the context of nutrition labels for individuals' food choices, the valence of feedback in the form of visual information, such as traffic light colors, influenced healthier food choices in food environments (Lobstein & Davies, 2009; Thorndike et al., 2014). Thus, we propose:

DG RIA 2: Provide timely assessment feedback to enable individuals to qualitatively judge relevant food choice criteria.

Schön (1983) describes "active experimentation" in a puzzling problem as a requirement to test several paths that can lead to an optimal solution. In this process, a supervisor can provide help to learners to find the "right" steps to achieve a solution by practical methods that relate to the problem field. Argyris and Schön (1997) further establish the important role that an external source plays in encouraging learners to test public evaluations and to avoid defensive behaviors such as advocating for undesired behavioral outcomes. The authors suggest that learners should consider multiple or contrasting views from an external competent knowledge source to help them examine "inconsistencies or gaps" in reasoning that supports the actions that have previously led to the problem they experience.

One's diet often relates to strong habitual cues that one can find difficult to break or interrupt as they emerge from lifelong learning, and individuals may maintain them due to defensive reasoning as long as they have no obvious health consequences. Instant feedback on behavior provides individuals with knowledge about how well they performed earlier. Despite the potential for performance feedback on behavior to increase personal awareness, we lack knowledge about how to implement activities based on provided feedback. Dietary practitioners often use feedback and recommendations based on personal diet assessment to offer guided practice and adaption towards healthier behaviors (Bauer & Liou, 2020; Glanz et al., 1995). Dietary and physical activity interventions have increasingly focused on providing instant and actionable feedback to engage users in implementing action to practice healthier behaviors (Schembre et al., 2018). Thus, we propose:

DG RIA 3.1: Provide actionable feedback through explicit, timely guidance to support users to act based on given food choice criteria.

Based on the literature on implicit and explicit communication (Yus, 1999), implicit communication requires contextual knowledge of the content, environment, and social or cultural environment to increase the probability of comprehending a message's intended meaning. Therefore, we deduce that one must make information explicit in unknown or new contexts that make predicting or interpreting an intended (implicit) message difficult. Additionally, our evaluations of artifact demonstrations with users indicated an inverse deduction of the intended explicit meaning. Thus, we propose:

DG RIA 3.2: Ensure users can correctly understand actionable information by providing an explanatory legend.

Table 1. RIA Design Guidelines (DG RIA)

Guidelines	
DG RIA 1	Provide a timely information context to help individuals make food choices by offering critical/important food choice criteria based on an individual's past behavior and external expertise.
DG RIA 2	Provide timely assessment feedback to enable individuals to qualitatively judge relevant food choice criteria.
DG RIA 3.1	Provide actionable feedback through explicit, timely guidance to support users in acting based on given food choice criteria.
DG RIA 3.2	Ensure that users can correctly understand actionable information by providing an explanatory legend.

3.1.2 Design Guidelines for ROA

According to Schön (1983), ROA means to reflect on past or finished actions to rethink and learn from these and related experiences to generate new knowledge and strategies to obtain a different, higher, or even meta-perspective about one's practice. Considering ROA as a form of double-loop learning, Argyris and Schön (1997) emphasize the role that transparency plays in producing valid information that one needs to obtain a different perspective.

People make dietary choices frequently every day. Furthermore, a personal diet follows individual routines and patterns that people perform unconsciously and, therefore, can find hard to remember. To critically judge dietary behavior requires that people consider their daily choices based on quality aspects because wrong or "unhealthy" choices over a longer time period can lead to undesired habits and risks for non-communicable diseases such as obesity, diabetes, coronary heart disease, and cancer (WHO, 2014). To judge personal dietary behavior for quality in nutritional science, researchers commonly break down nutrition behavior into assessable basic units such as contained nutrient intake levels (e.g., magnesium) (Thiele, Mensink, & Beitz, 2004). By analyzing nutritional intake levels, one can explore additional relationships such as dietary or meal patterns (Leech et al., 2015). Thus, we propose:

DG ROA 1: Transparently analyze an individual's dietary behavior by offering a structured overview of assessable criteria that relate to the individual's past dietary activities.

Schön (1983) proposes that a "reflective practitioner" reflects on action when the practitioner engages in rethinking a finished task or past actions by analyzing and comparing them to similar experiences to examine what led to undesired outcomes and what the practitioner could change in the future. This contemplation phase resembles the term relational transparency from Argyris and Schön (1997), who see transparent analysis as an important aspect or requirement to understand internal or non-obvious processes that lead to a certain strategy. To judge these processes and their interrelationship for quality and effectiveness, they emphasize that one needs additional valid knowledge, such as feedback from a sharing control. to help one contextually understand single actions and action strategies or patterns.

Daily routines and patterns that evolve through individual habits over time, which cultural and social contexts or personal factors (e.g., hunger or how much time and money one has) influence, frequently prompt food and nutrition decisions (Furst et al., 1996; Gedrich, 2003; Jastran et al., 2009). These factors do not necessarily lead to healthy choices. By monitoring one's own personal (dietary) behavior, one can externalize information and knowledge, which support their self-awareness and self-regulation skills based on past behavior (Li et al., 2010). As unhealthy behavior often relates to certain unobvious patterns, externalizing these patterns can benefit transparency and help individuals recognize them. From a nutritional science perspective, dietary patterns relate to an individual's food intake characteristics and the delivered nutrients (Tapsell et al., 2016). Basic nutritional intake levels from macro- and micronutrients represent valid and relevant health criteria to judge diet quality and provide a basis for deducing other relationships that relate to meals and their ingredients. To facilitate the assessment and draw conclusions for one's diet from a layperson's perspective, one requires a simple classification metric to extract the quality of certain repeated nutrient activities. Therefore, to qualitatively assess a person's past eating behavior, we propose classifying a person's past dietary actions into desirable and undesirable patterns. Thus, we propose:

DG ROA 2: Help individuals detect patterns by classifying valid assessable criteria units related to their past dietary activities.

Schön (1983) emphasizes that remembering (positive) experiences constitutes an important requirement to translate learned knowledge from experiences into future actions. Individuals can find it difficult to remember their personal diet from a time perspective. If the timeframe increases too much, individuals will probably forget what they have eaten. Thus, we propose:

DG ROA 3: Allow individuals to explore their eating habits and relationships between nutrients by displaying nutrient activities in a memorable timeframe.

Table 2. ROA Design Guidelines (DG ROA)

Guidelines	
DG ROA 1	Transparently analyze an individual's dietary behavior by offering a structured overview on assessable criteria that relate to the individual's past dietary activities.
DG ROA 2	Help individuals detect patterns by classifying valid assessable criteria units related to their past dietary activities.
DG ROA 3	Allow individuals to explore their eating habits and relationships between nutrients by displaying nutrient activities in a memorable timeframe.

3.2 Visual Design Patterns to Support Reflective Practice (Artifact 2)

In this section, we describe how we translated our proposed design guidelines into our final visual design artifacts (i.e., data-tracking interfaces) to promote healthier and balanced nutrition. To do so, we informed our design decisions with knowledge from the nutrition, visualization, and HCI domains and earlier demonstrations with users.

3.2.1 Translating RIA Guidelines into Artifact Design

To offer individuals a timely choice context (DG RIA 1) in personal tracking interfaces, we considered common display practices to design reflection in HCI and mHealth. Cuttone et al. (2014) suggest glancing overviews in displays as appropriate methods to offer information that requires timely analysis or quick interpretation. By framing the choice context to attentive behavioral aspects in terms of relevant or risk-related individual nutrient intake levels, we use *(re)framing*—a behavior-change technique from Abraham and Michie (2008) that suggests that one can adopt a new perspective on particular behavior to change one's cognitions or emotions about it. Our choice context provides a different perspective on dietary behavior as individuals normally assess their diet from more accessible criteria over the long term such as weight gain or control, perceived wellbeing, and taste. To ensure users could use a mobile screen, avoid information overload, and address attentive memory, we decided to offer a symmetric number of iconic images in the form of a representative overview of a user's most important/critical nutrients and their intake levels. Icons or iconic images represent a beneficial way to attract awareness and attention, according to research in health risk communication (Garcia-Retamero & Cokely, 2017) and ambient displays for lifestyle sustainability (Kim et al., 2010).

Our second guideline (DG RIA 2) requires timely assessment feedback to enable individuals to qualitatively judge relevant dietary choice criteria. A common behavior-change technique in the mHealth and personal informatics domains involves using performance feedback to assess previous behavior based on tracking data (Abraham & Michie, 2008; Schoeppe et al., 2017). Since personal dietary behavior and nutritional facts represent our choice context here, we relied on domain knowledge from nutrition science, behavioral economics, and public health policy. Researchers have found that offering nutritional information through traffic light schemes as part of nutrition labels have positive effects on individuals' behavior and the potential to reduce unhealthy food choices (Lobstein & Davies, 2009; Thorndike et al., 2014). Combining this knowledge with expertise from nutrition experts in our team, we decided to use the color coding scheme scientific dietary reference intakes adopt (DRI) (Meyers et al., 2006). Following this schema that resembles traffic lights, "green" refers to a nutrient with an optimal saturation state, "yellow" to a non-optimal state, and "red" to a critical nutrient state. We identified a visual pattern for implementing DG RIA 1 and 2 in which a set of relevant or critical behavioral criteria could represent an "instant-choice context" (see Figure 3) using iconic representations.

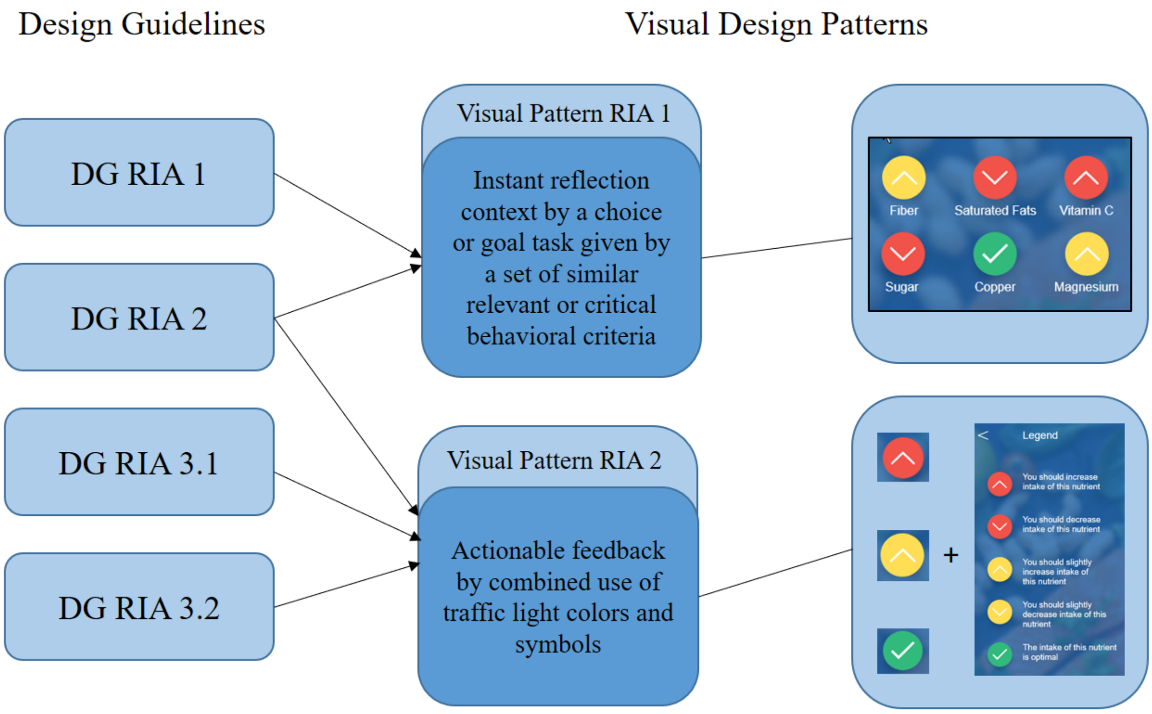

Figure 3. Translation of Design Guidelines into Visual Design Patterns (RIA)

According to our third RIA guideline (DG RIA 3), we need to encourage users to take dietary action after a visual interface presents their tracking data to help them gain new insights for solving problems. As we note above, assessment feedback via color codes allows users to make a general qualitative judgment, but it lacks other information that they can use to deduce meaning for action. Since nutrients can decrease, stay the same, or increase due to intake, we searched for a solution that maps to this behavior and displays a possible solution path towards a healthier choice based on this information. Healthcare professions use directional or corrective feedback in education to inform learners about what they need to correct (Archer, 2010). Furthermore, mHealth often provides nutritional assistance (e.g., recommending recipes) to assist people with nutrition. For use in a mobile visual display, we required an abstract representation that offers instructed feedback and direction. According to research in cognitive psychology, learning, and instructional design, visual cues can help guide users' attention and related reasoning processes (de Koning et al., 2009; Egeth & Yantis, 1997). Additionally, "provide instruction" represents a behavior-change technique that tells a person how to perform a behavior and/or preparatory behaviors (Abraham & Michie, 2008). Thus, we chose a simple arrow symbol to inform users about the direction they should take to achieve the desired action. As a result, we used an arrow facing up to mean users should increase how much they consume a nutrient and an arrow facing down to mean they should decrease how much they consume a nutrient. We further introduced a checkmark symbol to indicate that users had successfully consumed a nutrient at a sufficient level. We derive our second visual pattern, "actionable feedback" (see Figure 3), from combining traffic light color codes and symbols for directional feedback.

The final RIA design (see Figure 4) abstractly represents a potential problem space that provides guidance to achieve the desired solution (in our case, finding a way to optimize an individual's nutritional state). Results from mockup demonstrations reinforced DG RIA 3.2 as users tended to invert what we intended the arrow directions in the representation to actually mean. Therefore, we included an explanatory legend in the design (see Figure 4) according to the common practice in information visualization to externalize the given visual syntax (Tudoreanu & Hart, 2004).

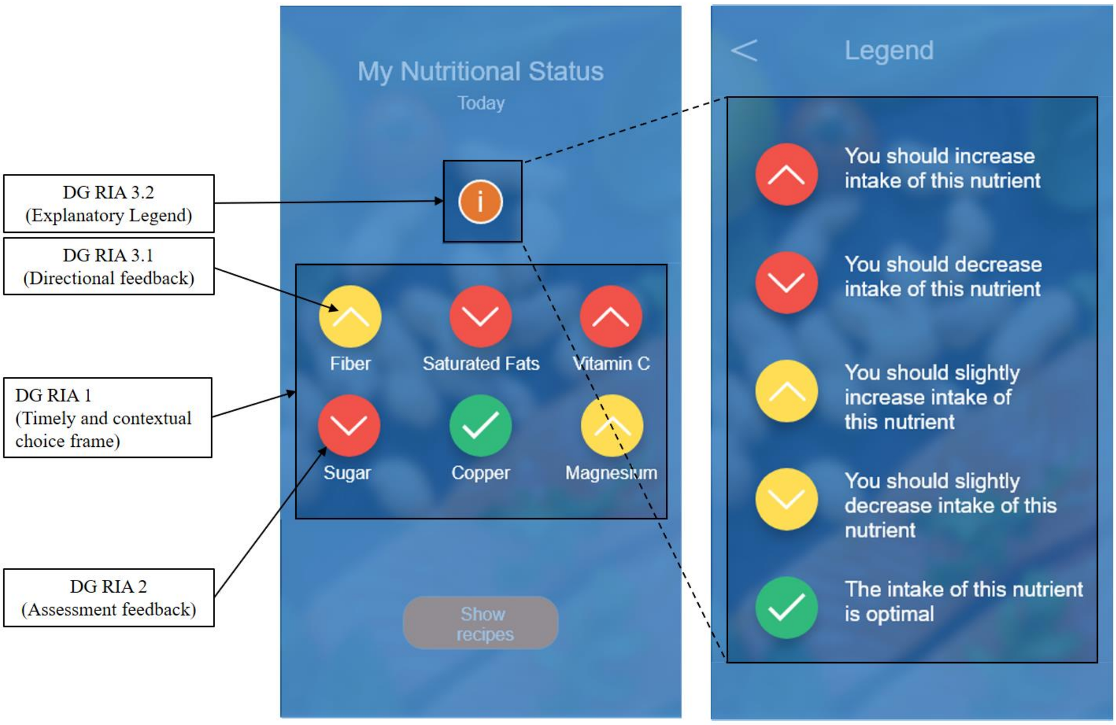

Figure 4. Final Mockup Artifact (RIA)

3.2.2 Translating ROA Guidelines into Artifact Design

To meet our first guideline for ROA (DG ROA 1) to offer a transparent information context, we relied on graphic trend lines, a standard mechanism in graphical displays. Trend lines offer a commonly proven way to discover numeric data and related temporal trends (e.g., for communicating health risks) (Ancker et al., 2006) to a wide range of individuals. Transparent visual aids that offer part-to-whole relationships play an important role in health risk information communication and health-related decision making (Garcia-Retamero & Cokely, 2017). To provide transparency on the structure and related components of an individual's diet in a mobile tracking context, we offer a transparent overview display of a relevant set of nutrients for judgment. We call this visual pattern "transparent inquiry" that breaks down the entire dietary behavior into similar diet-related assessment units (see Figure 5) at a more granular analysis level.

To translate our second guideline (DG ROA 2) into practical knowledge, we required a solution that allowed people to qualitatively judge temporal trends in tracking data. For this purpose, we combined highlighted trends by color in temporal graphs as the personal informatics domain recommends (Cuttone et al., 2014) with specific domain knowledge from nutrition science. As a result, we used the normative color codes from dietary reference intakes (DRI) from Meyers (2006) as the underlying background for graph data to more easily capture positive, negative, or sustained past trends in nutrient saturation.

To capture trends relevant to nutrient intake, the time interval to present data should not be less than three days. Based on how we translated our third guideline (DG ROA 3) and evaluations with mockup demonstrations, users preferred a time interval that spanned the past five weekdays (based on a choice between three, five, or seven days) to remember their past meals. Combining DG ROA 2 and 3, we introduce another visual pattern "weekly graph displays" to classify weekly nutrient actions and allow users explore relationships between nutrients and meals (see Figure 5).

Users also requested a selection-function for nutrients as they perceived the list as long and time consuming to capture and process the information. In the discussion with experts, we decided not to implement any selection or filtering function to display nutrients in order to maintain information transparency and avoid weighting certain nutrients more than others in the long term.

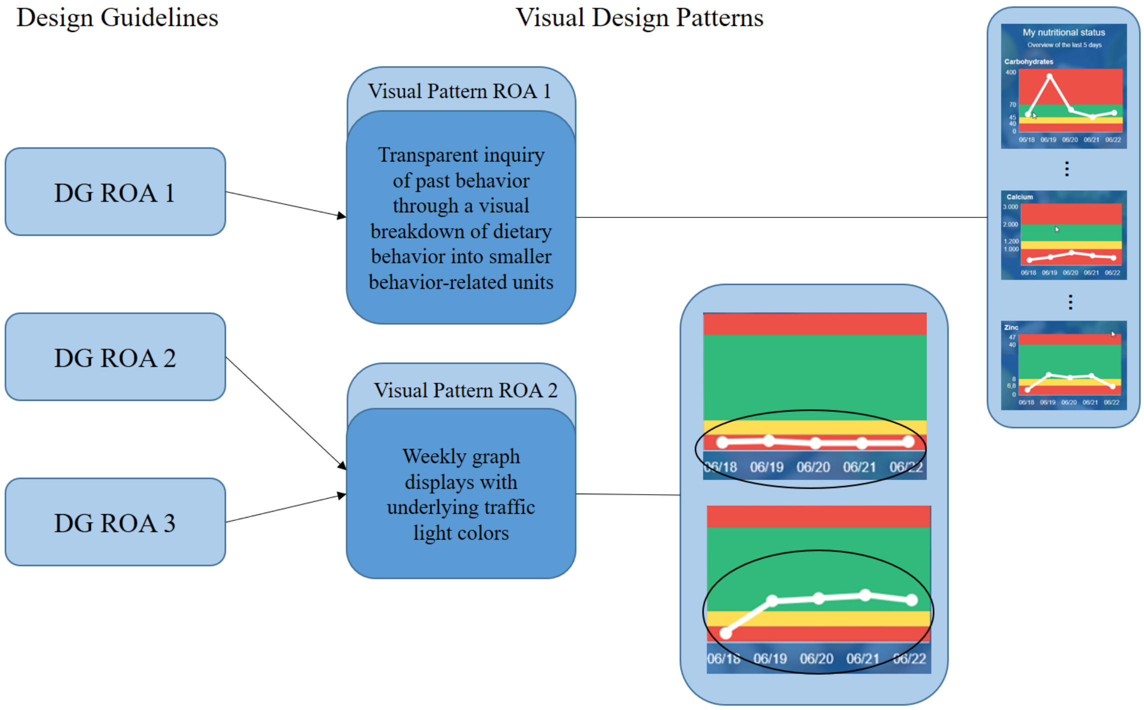

Figure 5. Translation of Design Guidelines into Visual Design Patterns (ROA)

Figure 6. Final Mockup Artifact (ROA)

4 Final Artifact Evaluation

To finally and formally evaluate our design guidelines in terms of artifacts, we conducted a laboratory experiment as a valid design science research method to assess their utility (Mettler et al., 2014). We defined the visual feedback that we incorporated in the two manifestations (ROA and RIA) as an independent variable to assess the outcome of choice quality in a task scenario. The experiment procedure included a user observation during artifact usage and a task scenario. The scenario included a choice task for a provided set of food recipes (see Section 5.2.1). Additionally, we asked questions to assess the extent to which participants perceived visual feedback representations as useful and the mockups' overall usability by including the standardized system usability questionnaire (SUS). The experiment followed a between-group design.

4.1 Experiment Design

4.1.1 Between-group Design

We chose a between-group design for the experiment to avoid learning effects when participants used the visualizations. We randomly assigned participants to each experimental group by preserving an equal distribution of female and male participants. The final groups comprised 32 participants for each visualization setting.

4.1.2 Recruitment and Participants

We recruited participants via online (i.e., Facebook and the Technical University of Munich's e-learning platform) and offline media channels (i.e., by directly asking students from the computer science department). In all, we recruited 64 participants with an equal distribution between female and male participants in each experiment group. The median age was 22 for the RIA group and 21 for the ROA group. Furthermore, 45 percent of the RIA and 42 percent of the ROA group participants had used a mobile health application before we conducted the experiment.

4.1.3 Apparatus and Materials

We used the following materials in the experiment: a handout for participants, a conversational guide and informational guide on nutritional values, the observational protocol, and hardware and software (visual mockups presented on a mobile device running iOS). The handout for participants contained information on the experiment's overall course. The experiment leader used a conversational guide that included the following three requests:

1) What do you see on the actual screen?
2) What does it mean?
3) You are welcome to first view the mockup, think about it, and then speak.

4.2 Experimental Setting and Procedure

We conducted the laboratory experiments for ten consecutive days in rooms at the computer science department at the Technical University of Munich. To ensure objectivity, we used the same setting for each participant (i.e., the same room, device, procedure, and experiment structure). The experiment contained five steps for each participant.

1) Reading handout on experiment conduction, steps, and settings
2) Verbal information from the experiment leader about the experiment and procedures
3) Viewing mockups presented on a mobile device
4) Fulfilling the user choice task
5) Answering questionnaire and open and closed questions concerning usefulness and usability.

4.2.1 Recipe Choice Task Scenario

We created a scenario to assess how visual feedback on nutritional outcomes influences the recipes that participants choose. They had to find the optimal order to rank recipes from a list based on the given personal nutritional state (see Figures 4 and 6). They could access the recipe list (offered as photos with a recipe title) through a button at the bottom of the screen. Participants could access recipe details by clicking an integrated link in either the photo or the recipe title. To adapt realistic settings, we offered recipes that lacked obvious differences in their nutritional character (see Figure 7). We selected the recipes we presented based on the personalized algorithm that Leipold et al. (2018) (researchers from the computer and nutrition science disciplines) developed for a mobile health recommender system. This algorithm matches recipes that fit an individual's nutritional deficits from the previous three days. The algorithm integrates individual variables such as the user's BMI, waist-to-hip ratio, age, and gender to personalize the nutrients (and, thus, weight) adjustments that it recommends to the user. The personalization also includes previous dietary intake. The offered recipe list contained two recipes that each belonged to four categories, such as green for optimal fit, yellow for almost optimal fit, orange for not optimal, and red for not at all a fit. Participants could not see these matching fit categories. To evaluate the decisions that users made to rank the recipes (based on a user-selected recipe's absolute distance from its position in the optimal recipe ranking vector), we defined a distance measure that denoted the ranking error per recipe (see Appendix A). To conduct the statistical analysis, we used R (version 1.1.463).

Figure 7. Recipe Screen Overview and Detailed Recipe View

4.2.2 Perceived Usefulness and Usability

We included questions to assess how users perceived the different visualization concepts and single representational elements for RIA and ROA (see Appendix A). The questions covered topics such as suitability, usefulness, and sensemaking. We further listed all SUS items (Brooke, 1996)—a standardized measurement instrument we could use to assess the overall usability score of both experiment groups.

4.3 Experiment Results

4.3.1 Perceived Usability and Usefulness of Visualizations

The participants rated the RIA experiment setting as excellent (77.8) and the ROA setting as good (73.3) (see Table 3) according to Bangor et al. (2009). The main difference among the distributions for the two groups concerned the range in values. The SUS values in the RIA group (47.5) had a smaller range than in the ROA group (52.5) (min. = 45.0 and max. = 92.5 versus min. = 42.5 and max. = 95.0, respectively).

Table 3. SUS Statistics

	Mean (SD)	Range (min/max)
RIA	77.8 (10.3)	47.5 (45.0/92.5)
ROA	73.3 (12.2)	52.5 (42.5/95.0)

To assess how useful the participants perceived the provided visual representation elements, participants used a five-point Likert scale to answer questions on visualization elements for RIA- and ROA-based feedback in terms of color, form, and symbol use. They clearly indicated that they perceived the external and internal visual cues in combination as the most helpful for the recipe choice task (see Figure 8). The percentage majority of the ROA group (53%) exceeds the one of the RIA group (44%).

Further, we independently assessed how well the RIA- and ROA-based feedback influenced participants' dietary behavior. Comparing the response numbers, we found higher agreement on ROA feedback, which suggests that ROA-based feedback provides users with more useful feedback on nutrition behavior in a timely context (see Figure 9). We could possibly attribute this response to elementary graph characteristics such as time development.

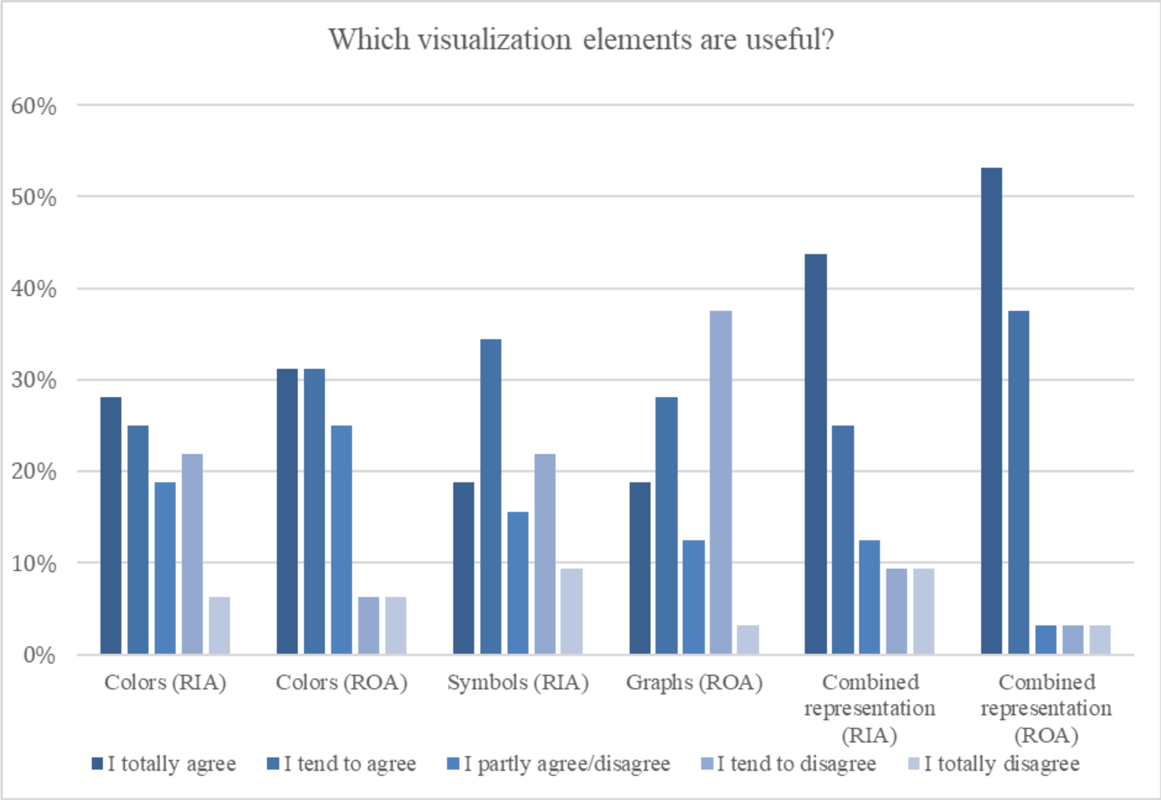

Figure 8. Perceived Usefulness of Visualization Elements in Experiment Groups (RIA (N = 32), ROA (N = 32))

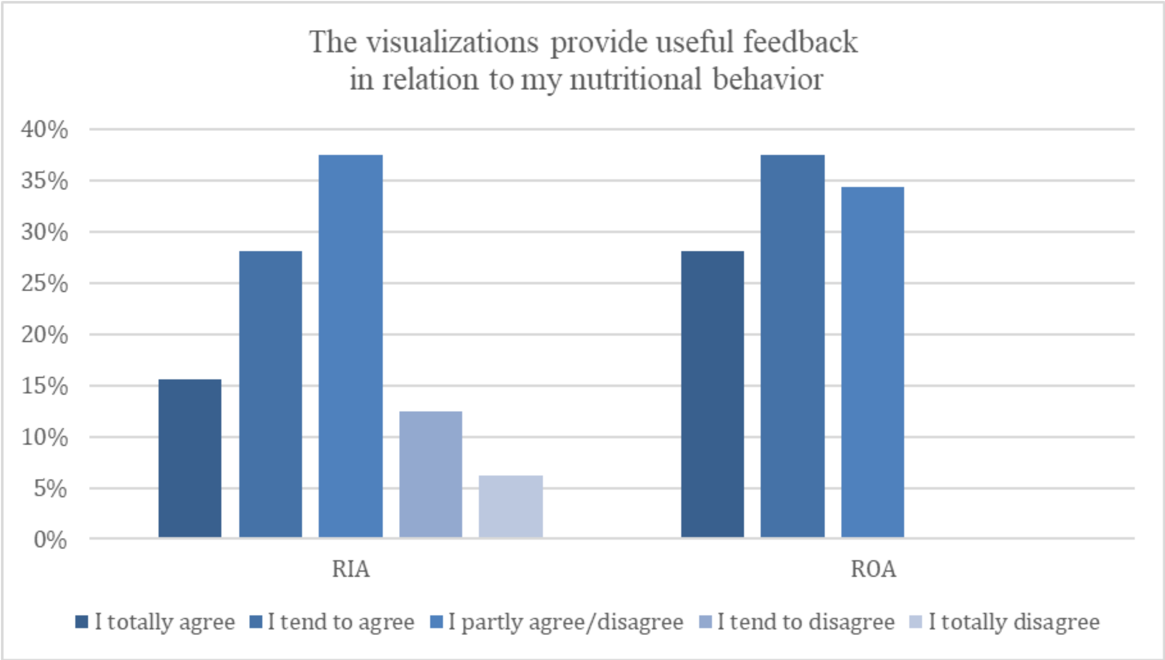

Figure 9. Perceived Usefulness of Visualizations regarding Users' Nutritional Behavior in Experiment Groups (RIA (N = 32), ROA (N = 32))

4.3.2 Recipe Choice Task Scenario Results

Given each group had two ranking-error distributions, we tested for normality by producing visual plots (see Figure A1 in the Appendix). Due to the visual nature of slight ordinal-scaled values, we calculated the Shapiro-Wilk normality test (p = 0.055, RIA; p = 0.291, ROA). We also calculated the one-sample Kolmogorov-Smirnov test (KS test), which resulted in a normal distribution with significant p-values for both group data sets (p-value < 2.2e-16 (RIA and ROA)). To assess which feedback setting (RIA and ROA) helped users understanding (based on their actions) the most, we compared RIA- and ROA-based mockups to each other. To do so, we needed to make hypotheses for both feedback contexts, which we present next. We assume that RIA-based feedback results in more appropriate food choices due to its actionable nature than ROA-based feedback. Thus, we hypothesized about variance unequality among the group distributions:

H1: RIA-based feedback supports recipe choices more appropriately than ROA-based feedback does: $\mathrm{Var}(\mathrm{RIA}) < \mathrm{Var}(\mathrm{ROA})$

We used the non-parametric Fligner-Killeen test, a rank-based test for homogeneity of variance, to test the hypothesis. Calculating the Fligner-Killeen test resulted in a significant p-value (med chi-squared = 7.071, df = 1, p = 0.009) based on a median-centered chi-square statistic. The resulting p-value (p = 0.009) rejected the test's null hypothesis of equal variances (i.e., homoscedasticity). Although this statistical test allows only for two-sided hypothesis testing, it is the most robust test statistic that corresponds to our data's character (i.e., non-normal, ordinal-scaled). Based on the given significance for group variance inhomogeneity $Var(RIA) \neq Var(ROA)$, we can assume that the RIA group had less variance than the ROA group: $Var(RIA) < Var(ROA)$. The group boxplots further support this conclusion (see Figure 10) since they show lower data variance from RIA-based feedback than from ROA-based feedback. For robustness and stability, we additionally calculated an ANCOVA based on the control variables SUS and perceived usefulness (PU). As a result, we identified a non-significant p-value for both control variables in the group setting for SUS (p = 0.0843) and PU (p = 0.0905).

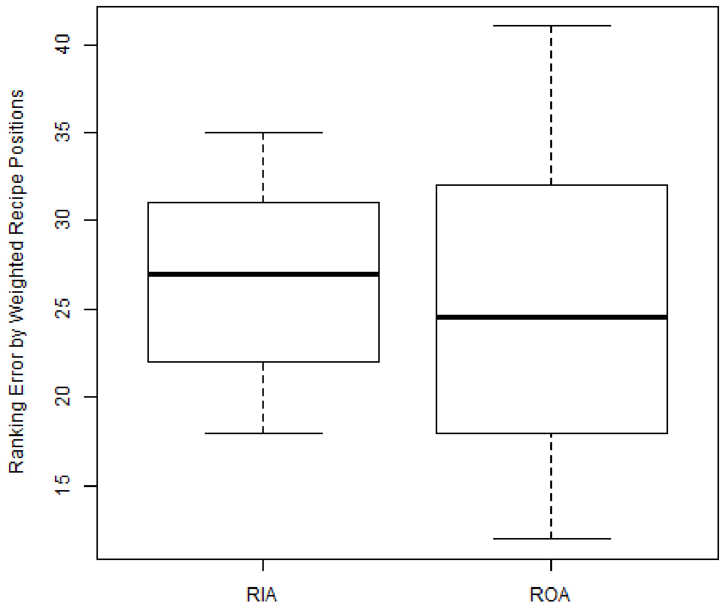

Figure 10. User Recipe Ranking Errors in Experiment Groups (RIA (N = 32), ROA (N = 32))

4.4 Overview on Design Guidelines for Reflective Practice

The results from prior evaluations with users and from our final artifact evaluation support the design guidelines that we derive in Section 4. In Table 4, we list our design guidelines, related references complementary to the theoretical core literature on reflective practice and learning, and contributing evaluation sources.

Table 4. Design Guidelines and Associated Sources

Design guidelines for RIA (DG RIA)		Related references	Evaluation sources
DG RIA 1	Provide a timely information context to help individuals make food choices by offering critical/important food choice criteria based on an individual's past behavior and external expertise.	Köster (2009), Garcia-Retamero & Cokely (2017), Bailey et al. (2015)	Informal and semi-structured interviews, experiment observation: The evaluation showed that users considered timely information useful for immediate choices.
DG RIA 2	Provide timely assessment feedback to enable individuals to qualitatively judge relevant food choice criteria.	Hattie & Timperley (2007), Sargeant et al. (2010), Balzer et al. (1989), Butler & Winne (1995), Faulkner (2000), Lobstein & Davies (2009), Thorndike et al. (2014)	Choice task, experiment observation: timely assessment feedback indicated its usefulness regarding the awareness and attention of specific choice criteria, perceived usefulness (see Figure 8)
DG RIA 3.1	Provide actionable feedback through explicit, timely guidance to support users in acting based on given food choice criteria.	Bauer & Liou (2020), Glanz et al. (1995), Schembre et al. (2018)	Perceived usefulness (see Figure 9), choice task
DG RIA 3.2	Ensure that users can correctly understand actionable information by providing an explanatory legend.	Yus (1999), Tudoreanu & Hart (2004)	Informal and semi-structured interviews, experiment observation: the evaluations showed that using a descriptive legend prevented users from misinterpreting the visual representations, choice task
Design guidelines for ROA (DG ROA)		**Related references**	**Evaluation sources**
DG ROA 1	Transparently analyze an individual's dietary behavior by offering a structured overview on assessable criteria that relate to the individual's past dietary activities.	Thiele et al. (2004), Leech et al. (2015)	Informal and semi-structured interviews: the set of timely nutrient trend analysis offered users additional and useful diet-related knowledge, perceived usefulness (see Figure 9)
DG ROA 2	Help individuals detect patterns by classifying valid assessable criteria units related to their past dietary activities.	Furst et al. (1996), Gedrich (2003), Jastran et al. (2009), Li et al. (2010), Tapsell et al. (2016)	Informal and semi-structured interviews, experiment observation: The evaluations indicated that classifying information help users detect positive or negative behavioral patterns, choice task, perceived usefulness (see Figures 8 and 9)
DG ROA 3	Allow individuals to explore their eating habits and relationships between nutrients by displaying nutrient activities in a memorable timeframe.	Schön (1983)	Informal and semi-structured interviews, experiment observation: users perceived a five-day timeframe as the most useful to associate eating behaviors and nutrient activities from data.

5 Discussion and Conclusion

In this work, we address the missing granularity and theory grounding in design for reflection as a process to support users in meaningful reflection contexts. We focused on two research questions:

RQ1: How can we develop a reflective practice using RIA and ROA in personal user interfaces for mHealth?

RQ2: Can the proposed reflection design help users understand personal data to provide actionable knowledge in terms of RIA and behavioral pattern analysis in terms of ROA?

First, to address how we can design for reflective practice in personal user interfaces to support mHealth promotion in nutrition, we developed theory-driven artifacts in terms of design guidelines and visual design patterns as part of an iterative design science approach (Peffers et al., 2007). With this approach, we could rigorously develop and test artifacts as instances of our initial design guidelines based on theoretical and domain knowledge. Second, to address whether the proposed design guidelines offer utility in terms of the different reflection settings, we compared short-term data analyses and longer-term data analyses. We found that our design guidelines offer utility according to their respective reflection context, using visual cues to enhance both visual and contextual comprehension of the underlying data.

As for in situ reflection for RIA, we offer actionable knowledge by using non-standard visualizations to help people perceive relevant health criteria and transform it into action. Results from our laboratory recipe choice experiment confirm the final RIA artifacts' "actionable" character. The experiment results indicated that users made better recipe choices from reading visual design patterns from RIA compared to ROA. We attribute this result to RIA artifacts' design characteristics as these artifacts provide structured and contextually relevant information (timely critical criteria in a choice task context) at hand. Current systems rarely incorporate concepts such as "reflection-in-action" (Epstein et al., 2020) and actionable feedback (Rabbi et al., 2015; Schembre et al., 2018), although research has identified their potential (Ploderer et al., 2014; Whooley et al., 2014). Finally, current research on visual cues, which indicates that visual cues can help users comprehend complex relationships and problem-solving related to learning tasks, supports our results (Klein et al., 2019; Kong et al., 2019).

Retrospective reflection with our final ROA mockup artifacts indicated their utility in that users found the highlighted areas in the temporal nutrient charts to be valuable and supportive in gaining their attention and in understanding the temporal relationship between nutrient values and consumed meals that were less than optimal. We conducted prior and final mockup evaluations under the hypothetical assumption that the users imagine the presented mockups as a personal display that shows their own past food intake. Results showed that the time interval in which the artifacts provided data affects whether users associate the data with their past meal experiences. Although individuals who used the demonstrations and the final experiment participants perceived the final ROA mockup artifacts as comprehensive, additional structure or support (i.e., through additional personalization, sorting, or filtering possibilities) in the presented data may have been helpful in helping them solve diet-related outcomes.

Our results from iteratively testing our design artifact confirm our initial theoretical assumption that structuring reflection design along RIA and ROA supports different aspects of the reflection process among users. In particular, our work highlights the value of actionable feedback based on behavioral criteria in a relevant choice context and as means towards healthier daily choices that can lead to behavior change in the long term. In addition, the visual design informs choices for healthier everyday practices and supports rethinking and learning from additional insights into previous dietary behaviors. Besides recommending that mHealth researchers and practitioners integrate both interrelated concepts into current mHealth apps, we highlight how RIA can influence users' daily choices as an entry point to achieve longer-term health behavior. Although focused on the applied health promotion context in HCI, our work might constitute a knowledge base beyond the health context such as designing comprehensible interfaces to help people understand relevant factors and choices related to individual or organizational finances, education, and learning.

5.1 Theoretical and Practical Implications

With this research, we make a theoretical contribution through developing design guidelines rooted in the theory of reflective practice as a relevant input for personal interfaces that help individuals reflect on their diet. According to Schön (1983), individuals need to make different experiences related to different "practicing" contexts such as taking action or acquiring a meta-perspective on past actions. We took this understanding as inspiration for our design approach to distinguish timely reflection contexts with different designs. Additionally, by synthesizing reflection as a double-loop learning process, we offer an extended perspective on designing for reflective practice to achieve deeper levels of user reflection based on visual feedback to personal tracking data by incorporating shared domain knowledge from IS and HCI. In line with Schermann et al. (2009), we use theory 1) as a basis for design artifacts, 2) to influence their evolutionary design process, and 3) as output for transferring and evaluating design knowledge.

Our work suggests several practical implications related to the HCI domain in terms of comprehensive user interface design to help users reflect on their behavioral tracking data. More concretely, it contributes to efforts to design interfaces that foster comprehensive and meaningful reflection, which constitutes a relevant step towards user transformation or behavior change (Fleck & Fitzpatrick, 2010). While reflective practice requires both reflection contexts (RIA and ROA), our results specifically indicate that RIA-based designs have potential in this area as they support users in a timely manner and provide actionable feedback.

According to Adam, Gregor, Hevner, and Morana (2021), design science research methods support three distinct modes in HCI projects (interior, exterior, gestalt) as proposed in their conceptual framework. We apply the gestalt mode of DSR, which integrates both the interior mode (i.e., designing, constructing, and evaluating visual data-tracking interfaces) and the exterior mode (i.e., proposing prescriptive, theory-driven design guidelines to support user behavior through interface design). By using the gestalt mode, we contribute to the improvement of both human behavior as well as components of IT systems in iterative cycles. By using the DSR methodology from Peffers et al. (2007), we successfully gained practical knowledge for reflection design in personal visual user interfaces from the iterative evaluation of theory-based artifacts. We intend for this design knowledge to assist researchers and developers in translating it into practical solutions to help users benefit from nutrition-related data representations in the form of healthier dietary choices. In relation to reflection design, a DSR approach allows one to “thoughtfully” design artifacts (Ghajargar & Wiberg, 2018).

Enhancing reflection that people experience via user interfaces’ visual elements pertains to HCI in general and to domain-specific personal informatics systems (i.e., transformative reflection) and mHealth systems (i.e., behavior change support). We highlight the role that the user interface plays as a medium in communicating health-related data in specific timely contexts to enhance individual reflective practice. As a result, our work raises different opportunities for designers and users. Using visual cues to highlight visual areas in an interface has the potential to help people learn and understand complex causal relationships and perceive risks (Klein et al., 2019; Kong et al., 2019; Peregrin, 2010). As health and nutritional relationships often result in complex settings related to user choices and decisions, to communicate relevant information in a simple manner may prove beneficial in various health and healthcare systems that use visual interfaces. Divided into different temporal contexts, our work proposes reconsidering traditional statistically driven visualization designs in order to support future users with help from contextually meaningful reflection on data. RIA (see Table 1) serves as inspiration for future design approaches for personal tracking data interfaces to support users’ problem-solving and reasoning skills with regard to their nutritional choices. As previous research has indicated, visual cues can help illiterate or poorly literate individuals to understand complex data representations or information (Garcia-Retamero & Cokely, 2013, 2017; Peregrin, 2010). As the increasing amounts of health data allow for retrospective analysis, DG ROA provides beneficial means to support standard trend analyses by visual pattern detection in nutrients. Existing systems that use reflection to promote behavior change mostly provide “open-ended” reflection rather than a more closed-ended perspective or guidance (Ploderer et al., 2014). Fleck and Fitzpatrick (2010) suggest structural mentoring to support teacher reflection and using reflective material rather than purely open-ended discussions. We refer to the above proposed structured, closed-loop reflection support through the recommendation of RIA and ROA for a visual data interface context.

We propose that mHealth researchers should consider reflection theory as relevant to mHealth system design. Although current research emphasizes that one integrates behavior change theory into app design due to its potential to change behavior (Salwen-Deremer et al., 2020), our results suggest reflection theory as an alternative or enriching way to view currently used behavior change models. Regarding the design and evaluation approach, our work differs from common mHealth design studies as they often take a long-term approach to prove or test primary or secondary health outcomes. We suggest that researchers should think about design evaluations that assess specific design aspects in terms of qualitative (perceived experience) and quantitative (actual behavior) user experiences since doing so prevents them from omitting important issues in evaluating visual designs and their effects. Considering both qualitative and quantitative evaluations might offer earlier insights into the interface or system design and help researchers understand extracted design criteria similar to research in information visualization (Blumenstein et al., 2016) or nutrition label use (Helfer & Shultz, 2014).

5.2 Limitations

As with any study, this one has several limitations. First, our participants represent a homogeneous group in that they had a similar educational background and study focus. Their age may have influenced their comfort in using digital programs and, as students, they have become accustomed to reading and interpreting graphics. We attempted to control selection bias by matching participants in the two groups. We recognized a need to have an equal number of females in both groups as women tend to be more attuned to and interested in optimizing and improving health than men (Pinkhasov et al., 2010). We did not know or assess the participants’ nutrition knowledge nor did we assess their health status (i.e., whether they had metabolic disorders such as diabetes). Since our findings constitute experimental knowledge, we extracted user experiences and behavioral choices rather than knowledge on behavior change. Hence, future research could examine how visual design affects users’ thoughts, actions, and behavior in a field setting over a longer period. Specifically, for ROA, researchers should evaluate user perceptions and actions related to long-term personal nutrition strategies. We suggest researchers investigate RIA and ROA in combination as these two reflection types relate to each other, and daily nutritional choices and individual nutritional strategies could emerge from both.

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Appendix A: Additional Experiment Information

Recipe Choice Task

Scenario: imagine that you would use the mockups just presented as an app. The app knows your food preferences, eating habits and body measurements. Which of the recipes would you most likely choose, which one least? Please sort the eight recipes by entering 1, 2, ... 8 in the field in front of the recipes, where 1 represents your optimal selection.

Important: the goal is to optimize your nutrient balance. Please leave out personal preferences and your own culinary skills when choosing! To answer this question, you can look at the mockups again. For further information, the information brochure “Additional information on nutrition” is available to you if required (printed out at the place).

___ Cold cucumber soup with crab

___ Chicken in soy sauce

___ Ham omelette

___ Mushroom pan

___ Fish soup from Mediterranean fish

___ Grilled zucchini in balsamic

___ Spinach and ricotta dumplings

___ Lamb shoulder with rosemary

Why did you choose this sequence?

Questions on Perception and Comprehension of the Visualizations

You are welcome to again look at the mockups to answer the following questions.

Table A1. Questions on Perception and Comprehension of the Visualizations

	I totally disagree	I tend to disagree	Partly, partly	I tend to agree	I totally agree
The colors in “My nutritional status” are helpful to answer the recipe choice task / The graphs in “My nutritional status” are helpful to answer the recipe choice task	o	o	o	o	o
The symbols inside the circles are useful to answer the recipe choice task / The colors inside the graphs are useful to answer the recipe choice task	o	o	o	o	o
The visualization mockup offers useful feedback in relation to my nutrition behavior.	o	o	o	o	o
I should intake more vitamin c.	o	o	o	o	o
I should intake less ferrum.	o	o	o	o	o
I don’t understand what the symbols inside the circles mean / I don’t understand what the graphs represent.	o	o	o	o	o
The combination of colors and symbols is not useful / The combination of colors and line graph is not useful.	o	o	o	o	o

Note: Table A1 contains questions for both experiment groups (RIA and ROA) separated by a “/”

General Information

Feedback about the presented visualizations: what did you like and what didn't you like? Do you have any suggestions for improvement?

Degree program: ____________________

Age: _______

Gender:

- o Female
- o Male

Have you ever used a health app (e.g. fitness tracker, nutrition diary, or for special diseases e.g. migraine app?)

- o No
- o Yes, namely: ____

Participant Demographics

Table A2. Participant Demographics

Experiment group	Age (years)		Gender (n)	Majors (n)
RIA	Mean (SD)	22.9 (4.4)	Male:16 Female: 16	MSc information systems (7), computer science (13), mathematics (10), physics (1), human factors engineering (1)
ROA	Mean (SD)	23.1 (7.80)	Male: 16 Female: 16	Information systems (15), computer science (12), Mathematics (2), physics (1), business administration (1), teaching studies primary school (1)

Distribution of Experiment Data Set

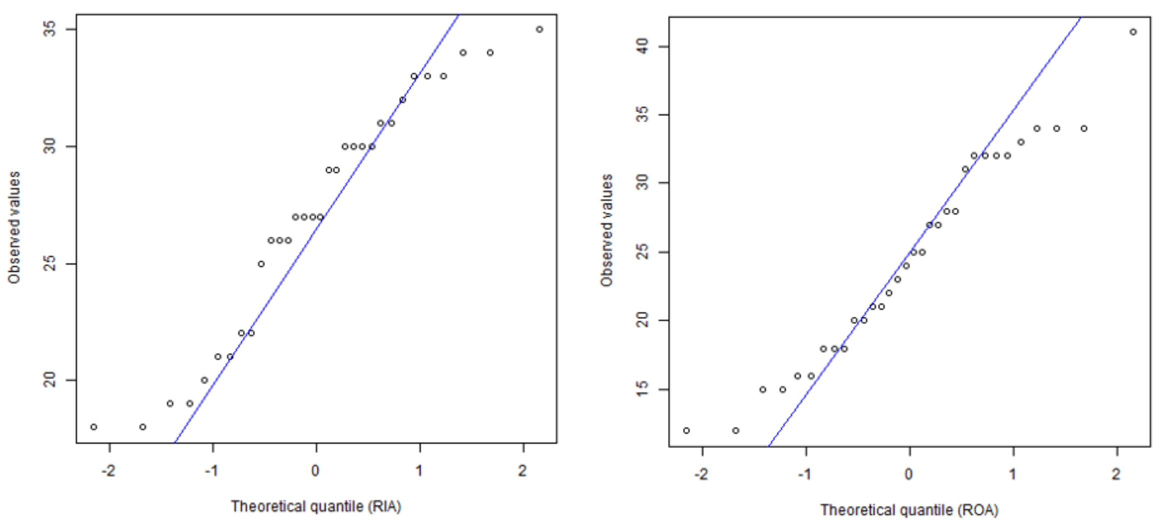

Figure A1. Normal Q-Q Plot of Recipe Ranking Errors in Experiment Groups (RIA (N = 32), ROA (N = 32))

Evaluation Measure for Recipe Ranking Distance

To achieve an appropriate distance measure, we needed to map the optimal ranking order for the eight recipes into four health equivalence classes with a descending order. (i.e., 1 = the most appropriate and 4 = least appropriate recipe/health equivalency class). Hence, we chose to offer two nutritionally equivalent meals to users to avoid choices due to taste and preferences. The four recipe equivalency classes comprised two equivalent matching recipes in terms of their nutritional appropriateness towards the nutritional status that the mockups provided but met different individual tastes. After mapping the original eight recipes into their equivalency classes, we calculated the absolute distance between each given user recipe position and its optimal position in the optimal recipe ranking. We formally denoted this distance as the optimal recipe-ranking vector:

$$\vec{r}_o = (1,2,3,4,5,6,7,8), \quad (1)$$

whereas a mapping into the four equivalency classes resulted in an optimal equivalent ranking vector according to mapping:

$$\vec{r}_{oeq} = (1, 1, 2, 2, 3, 3, 4, 4). \quad (2)$$

The vector $\vec{r}_u$ represents the ranking of recipes according to the perceived healthiness in descending order by the users:

$$\vec{r}_u = (ru_1, ru_2, ru_3, ru_4, ru_5, ru_6, ru_7, ru_8) \quad (3)$$

We then defined the distance from the optimal recipe ranking or alternatively ranking error for each user recipe choice as *ranking* error vector*:*

$$\tilde{r}_e = \left|\vec{r}_{oeq} - \vec{r}_u\right| \quad (4)$$

We further introduced a weighting function to emphasize the top-ranked items, which means that the recipes rated as healthier on the first entries of the ranking are weighted higher than the subsequent less healthy rated entries. The following vector schema subsequently weighed each entry in a given ranking-error vector (per recipe and user) in terms of a dot product, which results in a weighted delta:

$$\vec{w} = (4, 4, 3, 3, 2, 2,1,1) \quad (5)$$

$$\delta = \vec{w} * \vec{r}_e \quad (6)$$

We argue that upper entries should contribute more significantly to the overall user ranking than middle and lower entries according to the order in which each user ranked the recipes. This approach builds on our assumption that upper ranking results constitute a closer approximation to a final user decision for an optimal recipe than lower-ranking entries. Therefore, we introduced the following weighting schema:

$$w = \vec{w} * \vec{r}_e = (w_1 \vdots w_8) * (r_{e1} \vdots r_{e8}), \quad (7)$$

About the Authors

Nadja Leipold is a member of the research group Krcmar Lab at the Faculty for Informatics, Technical University of Munich (TUM). Currently, she is working in the field of mHealth where she focuses on effective design strategies for promoting individual health behaviors. Her research explores the potential and effect of theory-driven mHealth design on the awareness, motivation, understanding, and decision-making of users. Specifically, she is interested in personal information displays of health-related data to enable individual dietary behavior towards more healthful choices.

Hanna Hauptmann is an assistant professor at the Human-Centered Computing Group of Utrecht University. She previously (2019-2021) worked at the Data Analysis and Visualization group of the University of Konstanz on human-centered design for interactive intelligent systems by providing, among others, explainable AI, personalization, persuasion, guidance, and gamification. She received her doctoral degree (2020) at the Technical University of Munich (TUM) on building socio-technical systems for healthy nutrition. Part of her research was personalizing nutrition recommendations, according to both medical and social user profiles. She has co-organized five Health Recommender Systems workshops collocated with the ACM Recommender Systems Conference, supported the conference organization committees of RecSys and IUI, and reviewed for several workshops (HAPPIE, MuMe, HealthRecSys, UCAI), conferences (CSCW, UMAP, RecSys LBR, VIS), and journals (UMUAI, ACM Health).

Markus Böhm is Professor for Information Systems, in particular Digital Transformation at the University of Applied Sciences Landshut. He graduated in Business & Information Systems Engineering from Friedrich-Alexander University Erlangen-Nürnberg (FAU), and holds a doctoral degree in Information Systems from the Technical University of Munich (TUM), where he also served as research assistant, research group leader and interim professor between 2009 and 2021. Markus has a profound industry experience as analyst, project manager and software developer at among others fortiss, Siemens and Bosch. His research focus is on mergers & acquisitions, business model innovation and digital transformation. Markus co-authored more than 150 research papers published in all major IS conference proceedings as well as IS, Informatics and Business Journals including European Journal of Information Systems, Electronic Markets, MISQ Executive, the Journal of Systems and Software, the Journal of Business Economics and Business & Information Systems Engineering. Markus was listed among the top 5 % of the most research-intensive business economists in German-speaking countries according to the 2020 WirtschaftsWoche ranking.

Mira Madenach is a Ph. D. student at the Technical University of Munich (TUM) in the area of nutrition science. Her research focuses on using mHealth approaches in the area of personalised nutrition to provide a user-friendly and effective tool to promote healthy nutrition by influencing dietary behaviour. She also worked on methods to use dried blood spot samples to integrate them in the personalised mHealth strategies. Dried bloods spots can provide additional information on the nutritional status of a person to improve the personalised dietary feedback. Next to publications on personalised nutrition using mHealth, she also published a paper in the area of nutrigenetics and its feasability in practice.

Martin Lurz is part of the research group Krcmar Lab at the Faculty for Informatics, Technical University of Munich (TUM). Currently, he is working in the field of mHealth where he focuses on providing personalized information for promoting individual health behaviours. His research explores the potential and effect of coarse dietary data in conjunction with a user’s other environmental data to generate personalized interventions to enable users to make more healthful food choices.

Georg Groh is currently heading the Research Group Social Computing at the Faculty for Informatics, Technical University of Munich (TUM). He holds Diploma degreees in theoretical Physics and Computer Science. During his PhD on Ad-Hoc Groups and Habilitation on Contextual Social Networking his research focused on Machine-Learning- and NLP-based modeling, inferrence, and application of of short-term and long-term social context in socio-technical systems. This encompasses audio-based and interaction geometry based social situation modeling, social network analysis, or socially related user-modeling e.g. in terms of interests. The current research projects in his group include socio-technical systems supporting a healthier lifestyle, machine learning based NLP for opinion mining, knowledge-based recommender systems, topical influence on the web and hate speech detection and explainable AI.

Kurt Gedrich is a professor at the Institute for Food & Health at the Technical University of Munich (TUM) and head of the Research Group Public Health Nutrition. His research interest is focusing on 1) assessing food consumption and dietary patterns in various population groups; 2) understanding determinants of dietary behaviour; and 3) supporting healthy dietary choices under both conditions, food abundance as well as food scarcity. A particular challenge is the double burden of malnutrition, i.e. the simultaneous manifestation of over- and undernutrition in individuals.

Helmut Krcmar is a German IS and Management scholar. Since 2020 he leads the research group Krcmar Lab at the Faculty of Informatics, Technical University of Munich (TUM), Germany. From 2002 to 2020, he held the Chair for Information Systems, Faculty of Informatics at the Technical University of Munich. Before 2002, he was Chair for Information Systems, Hohenheim University, Stuttgart. Helmut is an AIS Fellow and has served the IS community in many roles, including as President of the Association for Information Systems. His research interests include information and knowledge management, service management, business process management, and business information systems. His work has appeared in Journal of Management Information Systems, Journal of Strategic Information Systems, Journal of Management Accounting Research, Journal of Information Technology, Information Systems Journal, and Wirtschaftsinformatik.

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