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Evaluating design approaches for encouraging behavior change in editors: exploring a digital nudging strategy in a non-personalized recommender system to promote adoption of augmented analytics

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Abstract

In the age of digitalization, navigating through vast amounts of data is a challenge. Augmented analytics, which often goes unnoticed by employees, has the potential to support effective decision-making. This study examines the impact of digital nudging on editors' cognitive load and behavioral change towards augmented analytics, providing insights into behavior change design. Combining theory with expert interviews and workshops, this study results in five nudging strategies. The findings reveal varied triggers influencing behavioral change, emphasizing stakeholder involvement in the process.

Keywords: behavioural design, decision making, digital nudging, user-centred design

1. Introduction

Human life is entangled with manifold decision-making. Given the estimated 20,000 decisions a person makes every day, according to Ernst Pöppel, Professor of Medical Psychology in Munich, Germany, in 2008, behavioral science aims to clarify the brain's ability to cope with this cognitive load without succumbing. Behavioral science has gained significance in both design and business domains as it provides valuable insights into human behavior and the cognitive heuristics employed for decision-making.

Understanding stakeholders from a business perspective is critical to effectively influencing their behavior. Beyond behavioral science, the advent of Big Data poses challenges for companies in terms of strategy planning and adapting to dynamic stakeholder behavior. The proliferation of these technologies is heightening the difficulty for businesses to handle copious amounts of data and make informed decisions using conventional methods that would enhance the company's competitive advantages. Consequently, experts from Business Intelligence (BI) are increasingly utilizing data-driven decision-making approaches to efficiently process, analyze, and visualize large datasets, facilitating rapid decision-making and ultimately conferring a competitive edge.

These data-driven decision-making processes are increasingly empowered by analytics. These automated processes are particularly adept at comprehensively evaluating this data and making decisions based on it, which would be impractical to achieve through traditional methods due to their velocity. However, not every employee within a company perceives the advantages of what is referred to as Augmented Analytics. This is where a need for Design for Behavior Change arises, to persuade employees to embrace these benefits without coercion and to assist them eliminate repetitive tasks from their work lives.

This study was carried out in collaboration with Ippen Digital to explore how design methods can be utilized in employee-related settings. Ippen Digital, a leading IT service provider with a network of over 80 portals serving publishers and media entities throughout Germany, aims to significantly impact the digital transformation of the news industry. Their goal is to improve the functionality and appeal of the publishing sector, benefiting not only their organization and workforce but also extending these advantages to corporate publishers and the readership at large.

Currently, Ippen Digital concentrates on technological advancements geared towards streamlining editorial processes. These innovations involve machine-learning systems that excel at handling routine tasks, thereby enabling journalists to redirect their efforts towards more creative endeavors. The company is actively experimenting with nearly 30 diverse algorithms in areas such as optimizing data evaluation, distribution, and personalized layout creation. Furthermore, Ippen Digital emphasizes the importance of nurturing editorial collaboration and interconnectivity among publishers.

2. Theory and concepts

2.1. Psychology and economics

The application of psychology and behavioral science in business involves implementing nudges to influence immediate behaviors and emotions, extending contextual impact. Despite the concealed advantages, companies have historically relied on static models of rational economic human behavior for strategic revenue objectives (Khan and Newman, 2021).

Studies in psychology and economics reveal that decision-making is influenced by psychological effects stemming from evolutionary and neurological origins, encompassing both conscious and unconscious processes (Mirsch, Jung, et al., 2018).

Human decision-making, characterized by the dual-process theory of System 1 (intuition) and System 2 (reasoning), is fundamental to psychology and behavioral science. The brain's evolutionary preference for efficiency relies on System 1 for most daily decisions, leading to a dominance of emotional and irrational factors (Dolan et al., 2012; Spreer, 2018).

Behavioral economics, exploring cognitive heuristics and biases, challenges the profit-centric view, emphasizing the pursuit of satisfying outcomes and bounded rationality. Bounded rationality recognizes the limited cognitive resources available to individuals during decision-making and underscores the significance of heuristics that simplify the decision-making process. Heuristics and biases wield influence across decision-making domains. Biases, originating from systematic thinking errors linked to information processing errors, introduce distortions. In contrast, heuristics serve as cognitive shortcuts, streamlining decisions, especially in uncertain contexts. They are pragmatic shortcuts, not optimization strategies, demanding minimal cognitive effort. This interaction between heuristics and biases occurs within the decision-making process, involving both systems (Roy et al., 2021; Thaler and Sunstein, 2008).

Over time, the evolution of understanding decision-making processes has led to knowledge about different prevailing heuristics, to name a few: Status quo bias, or inertia, reflects a proclivity to resist change and favor the path of least resistance. Loss aversion reinforces this bias, inducing aversion to losses and emotional reactions. Framing, a significant heuristic, shapes decision-making based on the presentation of information (Caraban et al., 2019; Lockton, 2012; Thaler and Sunstein, 2008).

2.2. Introduction to analytics

The rise of digitalization has simplified lives, increased data collection, and heightened the importance of advanced analytics tools for decision-making. With a focus on customer-related data, businesses invest in analytics to unveil valuable insights, enhancing decision-making beyond the capabilities of traditional methods (Alghamdi and Al-Baity, 2022).

Data-driven decision-making involves prescriptive, descriptive, diagnostic, and predictive techniques tailored to different decision types. Descriptive analytics visualizes historical and current data, while diagnostic explores root causes based on historical data. Predictive analytics forecasts future events, and prescriptive optimizes performance (Gartner, n.d.; Ghavami, 2020; Vassakis et al., 2018).

Gartner introduced "augmented analytics" (AA) in 2017 as a contemporary approach. Currently, BI professionals not employing augmented analytics may spend up to 80 percent of their work time on data-related tasks, emphasizing the need for new technologies (Guarda and Lopes, 2023).
Augmented analytics (AA) is closely linked to existing analytics categories, encompassing all types. It provides a transformative advantage in BI by leveraging AI, machine learning (ML), and natural language processing (NLP) to aid in data preparation, insight generation, and explanation within analytics. With AI consistently active, AA can swiftly detect sudden metric changes, offering quick access to data-driven insights. This ensures a neutral perspective by revealing concealed insights and mitigating human bias (Andriole, 2019; Gartner, 2017a; Guarda and Lopes, 2023).

2.3. Design for behavior change

Designers exert influence over human behavior. This raises the question of how insights from behavioral sciences can be effectively integrated into design to promote lasting changes in user behavior.
In the context of designing for behavior change, biases, and heuristics play a significant role. Designers can leverage these cognitive effects to influence behavior directly or strategically circumvent them to encourage better decision-making. Understanding heuristics is valuable in establishing new behavioral patterns within designed systems. It enables designers to create products or systems that minimize cognitive load, enhancing accessibility and practicality. This knowledge empowers designers to consciously shape human behavior and comprehend the underlying reasons for decisions, contributing to their increased influence and responsibility in promoting positive social behavior through human-centered design (Hunnes, 2016; Lockton, 2012).

2.4. Nudge theory

The concept of nudging arises from the idea that people often find themselves in situations where experienced professionals dominate, making it challenging for novices to make sound decisions. Effective decisions are typically made in familiar environments with experience and immediate feedback. In unfamiliar contexts, nudges can positively influence people's behavior (Thaler and Sunstein, 2008).
While many Human-Computer Interaction (HCI) technologies focus on engaging the reflective System 2 in behavior change, nudging operates differently by utilizing the fast, intuitive processes of System 1. Despite extensive research on nudging, there is still a need for more knowledge on how to design effective nudges in real-world settings, with existing understanding largely centered on the "why" rather than the "how" (Caraban et al., 2019, 2020).
To comprehend the concept and underlying rationale of nudging, it is crucial to explore different models and frameworks. Nudging, which draws from behavioral economics, gained prominence after the publication of Thaler and Sunstein's book 'Nudge' in 2008. It guides human behavior in politics and other contexts without coercion. This approach contends that design elements in the environment, within choice architecture, can subtly influence human decisions. Designers, as choice architects, shape the decision-making framework, making every design non-neutral. Nudging aims to change behavior for the better without coercion, a philosophy termed Libertarian Paternalism. It respects freedom of choice while decisively directing individuals towards more advantageous decisions. Utilizing behavioral science, cognitive heuristics, and biases, Libertarian Paternalism harnesses psychology to achieve its goals. Thaler and Sunstein define a nudge as *"an aspect of choice architecture that predictably alters behavior without prohibiting options or significantly altering economic incentives, and it must be easy and inexpensive to avoid*" (Thaler and Sunstein, 2008, p. 6).
In addition to the previously mentioned heuristics and biases in behavioral economics, nudges leverage various psychological effects, including the significance of social norms and herd affiliation. Social norms influence people's behavior, and social influence can be wielded through strategic information dissemination and peer pressure. When individuals are uncertain about how to act and seek social proof, nudges from trusted sources can be effective in guiding their decisions (Karlsen and Andersen, 2019; Thaler and Sunstein, 2008).
Efforts have been made to develop practical models for the effective implementation of nudges. One such model is the MINDSPACE framework, which comprises nine heuristics (Messenger, Incentives,

Norms, Defaults, Salience, Priming, Affect, Commitment, and Ego) that have demonstrated an impact on human behavior. However, there is a lack of long-term studies evaluating the effects of interventions based on the MINDSPACE model, highlighting the need for further research in this area (Eichhorn and Ott, 2019; Mejía, 2021).

2.5. Advanced nudging: Digital and smart nudging

People's lives and decisions are increasingly taking place in the digital space.
The digital age has led to information overload and hasty decision-making, impacting human behavior. Technology utilizes algorithms and recommender systems to automate and enhance decisions, profoundly digitizing choice architecture. Consequently, the term 'digital nudging' has emerged, signifying the increasing use of nudges in the digital realm (Mirsch, Lehrer, et al., 2018; Sobolev, 2021).
In 2016, Weinmann et al. introduced the concept of digital nudging, defining it as *"the use of user-interface design elements to guide people's behavior in digital choice environments"* (p. 433). Meske and Potthoff (2017) expanded on this, emphasizing the preservation of free choice. Their definition of digital nudging involves using design, information, and interaction elements to guide user behavior in digital environments without limiting individual freedom of choice.
Digital nudges employ similar psychological principles as traditional offline nudges, including status quo bias, social norms, loss aversion, anchor effects, and hyperbolic discounting. However, digital nudges offer advantages such as ease of implementation, cost-effectiveness, and better response analysis. They can be personalized and tailored to individuals, their preferences, and their circumstances, utilizing data and technology. With advancements in machine learning and AI, digital nudging is expected to become even more precise and efficient in guiding choices (Mirsch, Jung, et al., 2018; Sobolev, 2021).
Digital nudges can reach a broad user base and can provide personalized guidance by analyzing a user's current behavior and situation. This personalized and context-aware approach, known as 'smart nudging', tailors behavior guidance to each user's current situation (Karlsen and Andersen, 2022). Digital and smart nudging is not a one-size-fits-all solution due to its adaptive nature. It requires current information about the individual and their context. Several components, including the desired behavior, psychological effects, and delivery methods, work together to guide users towards the desired actions (Dalecke and Karlsen, 2020).
As with physical nudges, there have been efforts to develop models and methods for evaluating digital and/or smart nudges that can guide practical use. In contrast to previously developed models, the Mirsch, Lehrer, et al. (2018) model aims to offer a conceptual framework for designing digital nudges. Notably, this model considers the user requirements related to User Interface (UI), User Experience (UX), and digital services. The distinguishing feature of this model is its acknowledgment of the importance of engaging stakeholders in the development process, ensuring their involvement at every stage, which holds substantial value within a corporate context. The resulting Digital Nudge Design (DND) method encompasses four distinct phases: 1. Digital Nudge Context, 2. Digital Nudge Ideation and Design, 3. Digital Nudge Implementation, and 4. Digital Nudge Evaluation. In Phase 1, the technology channel and nudge objectives are defined. Phase 2 involves comprehending digital nudge principles, referring to established frameworks like Dolan et al., and selecting a nudge accordingly. Phase 3 focuses on implementing the chosen digital nudge within the designated technology channel, allowing for a minimum viable product to initiate a valid test. The last phase assesses the nudge's success by measuring its impact on the desired behavior through pre-defined Key Performance Indicators (KPIs).

3. Methodology

The main research question addressed in this study is: "To what extent do digital nudging design approaches reduce cognitive load and promote behavioral change among editors towards the use of augmented analytics in their work processes, and how do these design approaches influence editors' perceptions and attitudes towards the use of these tools?", while the hypothesis to be proven is: "Nudging helps the company to steer employees' behavior in the desired direction without the need to use coercion".

The practical framework discussed is the Editorial News Assistant (ENA) product initiative by Ippen Digital's Business Intelligence team, launched in late 2019. ENA serves to streamline editorial teams' work by automating repetitive tasks and enabling a focus on more critical activities, such as writing articles. It operates as a non-personalized recommendation system, utilizing analytical data from the company's internal database and applying rules for analysis to act upon.

Recommender systems are software tools and methods tailored to provide personalized recommendations to users, reducing the effort needed to find desired items. These systems offer value through customized suggestions. They can impact decision-making by managing the information accessible to users, automatically curating and presenting content (Jesse and Jannach, 2021). On the other hand, non-personalized recommender systems such as ENA offer the same recommendations to all their users in the target group. They select their items for a recommendation based on different criteria (Gena et al., 2019).

This study follows the interpretivist paradigm, emphasizing the importance of capturing diverse individual perspectives and allowing participants to express their subjective views and experiences, promoting a deep understanding of their assessments and communication with the researcher. It is underpinned by qualitative research, which is influenced by the philosophical assumptions and perspectives of the researchers conducting the study. Grounded theory, developed by Anselm Strauss and Barney Glaser in 1967, is a prominent qualitative research approach that challenges the appropriateness of prior research theories for the subjects under study (Creswell, 2007).

Qualitative data in grounded theory research can be obtained through various methods such as interviews, document analysis, observation, and ethnographic fieldwork. Grounded theory's flexible approach also permits the integration of diverse research settings and cognitive interests by incorporating different research methods (Strübing, 2022). Therefore, to support the qualitative research of grounded theory, methods of the design thinking process are also used in this study.

4. Findings and results

As this is an excerpt from a larger study, it was decided to list the key methods used for obtaining results. These primarily included the encoding process of expert and stakeholder interviews, the application of the Digital Nudge Design Method within the company, and a subsequent participatory workshop with stakeholders and experts to generate both qualitative insights and an executable design basis for the strategy that Ippen Digital can build upon.

4.1. Encoding process of interviews

In this study, a sample of nine individuals was interviewed using a semi-structured format. These participants were selected from diverse backgrounds, including: three experts from the Business Intelligence (BI) team, an expert in Artificial Intelligence (AI) and Natural Language Processing (NLP), two stakeholders from the Network Team (responsible for product rollout), and three journalists in varying positions. The analysis process aimed to compare interviewees' perspectives, starting with coding categories based on the interview questions. These categories included 'Nudges' and 'Satisfaction/Opinion', with the latter serving to gauge respondents' inclinations (positive, negative, neutral). An emphasis was placed on the 'Satisfaction' category to ensure alignment between coded segments and codes, facilitating subsequent comparisons. Further subdivision of the 'Nudges' category was carried out, breaking down digital nudges into common heuristics and making them more comprehensible to interviewees. Ten nudge categories were created as codes. It was ensured that only one code was assigned to each nudge per interview. The 'Satisfaction/Opinion' category revealed predominantly positive sentiments in the ENA environment, with negative comments being rare. The following findings provide an overview of the suitability and reception of different nudge options among interviewees, emphasizing the importance of further evaluation for certain cases:

1. Herd Instinct: Received unanimously positive feedback.
2. Status Quo Bias: Strongly disliked by all interviewees, best to avoid.
3. Informing: Generally seen positively, except for one neutral response.
4. Inertia: Mixed opinions, favored by experts but divided among stakeholders.

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5. Loss Aversion: Like inertia, mixed responses, more favorable in the network team.
6. Social Norms: Positive responses from both groups, indicating social factors' strength.
7. Reminder: Mixed feedback, potential benefits for newcomers but requiring further evaluation.
8. Feedback: Experts were positive, stakeholders favorable, with varying views on timing.
9. Framing/Position: Deemed less relevant, as the ENA is already prominently placed.
10. Superior Social: Mixed opinions, with varying responses to supervisor-led promotion.

4.2. Applying the digital nudge design (DND) method

Consolidating the collected impressions and nudge ideas to formulate potential nudges, the Digital Nudge Design Method (DND) by Mirsch et al. (2018) was selected for this purpose, primarily due to its suitability for implementation in a business environment. Mirsch et al's DND method is divided into four distinct phases: Context, Ideation and Design, Implementation and Evaluation. As the last two phases are highly dependent on the company's quarterly objectives and resources, the method was initially reduced to the first two steps. The initial phase involved outlining the context and framework of the digital nudge, following the DND approach. This included setting goals and selecting the technology channel for nudge delivery, with a primary focus on Google Space and ENA. The strategy aims to increase ENA utilization and gain a competitive edge to enable editors to allocate more time to user-centric article writing.

The subsequent step was to define the desired user behavior and key performance indicators (KPIs). The nudge's objectives encompass promoting daily and routine usage of ENA, discouraging self-publishing, encouraging user feedback, and positioning ENA as an independent "brand" through its features and overall functionality.

The analysis of user characteristics and decisions had already been presented in other parts of the larger study, so this step of the DND process could be omitted, and the second step of ideation and design could be performed. During the ideation phase, the study followed the approach of Mirsch et al. and applied Dolan et al.'s MINDSPACE framework. The goal was to understand and identify an appropriate technique or nudge for each automatic psychological process. In response to interviewees' disapproval of defaults and the status quo bias, these elements were excluded from the MINDSPACE framework. To maintain an overview, the DND method was applied as follows: Firstly, the heuristics were extracted from the interviews and broadly categorized into 'positive' and 'neutral/negative'. Index cards were then used in the bottom row to sort the strategies correctly to apply the MINDSPACE framework correctly. This ensured that the strategies matched both the framework and the heuristics from the interviews. This led to a list of ten strategies. Arrows in the infographic were used to connect nudge ideas that could relate to multiple heuristics for simplification in the next step (Figure1).

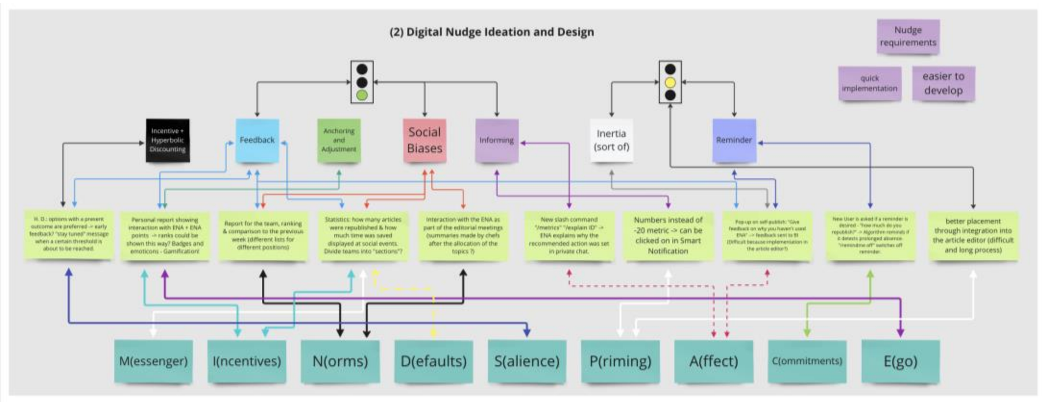

Figure 1. Ideation and design process part 1 of digital nudge design model

To prioritize and further develop the nudges in the subsequent phase, they were categorized into 'Text/Speech' and 'Text + Visual/Social'. This categorization considers the research on how stimuli can trigger different reactions in individuals. It takes into account their preferences for text, speech, visual,

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social, or other forms of stimuli, as shown in Figure 2. The aim was to develop strategies incorporating as many triggers as possible to increase potential impact and cover the widest possible audience.

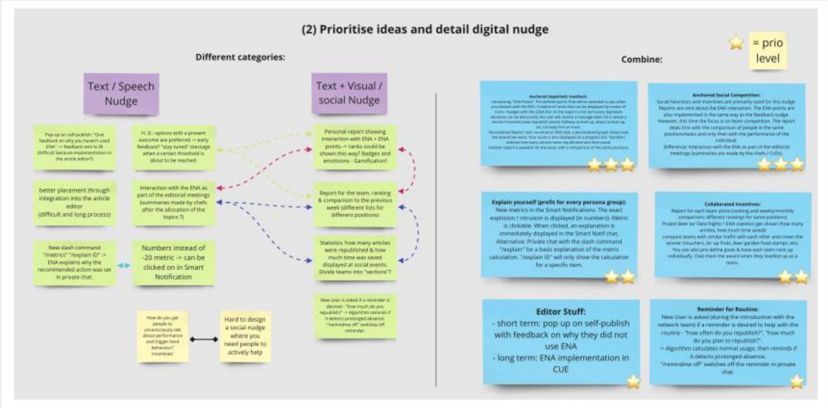

Figure 2. Ideation and design process part 2 of digital nudge design model

Given that interviewees responded favorably to the social and feedback aspects of nudges, an effort was made to combine these elements to create comprehensive nudges. This was particularly relevant because social nudges, driven by aspects like herd instinct, can be challenging to control without explicit instructions.

A total of six different nudges were developed and prioritized at the end of the ideation phase. Only the two strategies identified as the most promising through an evaluation with experts will be elaborated upon here. The criteria for prioritization were implementation time, degree of difficulty, and likelihood of success as measured by stakeholder and expert interviews:

1. **Anchored Hyperbolic Feedback** – Introducing 'ENA Points', where predefined points are awarded for interacting with ENA, allowing users to earn ranks and display them with icons or badges via the LENA bot. Users will receive notifications when they reach specific point thresholds to keep them engaged. A personalized report, delivered via email or ENA chat, includes a graph illustrating interaction data, a progress bar displaying the user's score, and information on republished articles and time saved. A separate team report compares user positions.
2. **Anchored Social Competition** – This nudge leverages social heuristics and incentives, mainly through reports on ENA interactions and the implementation of ENA points with a focus on team competition. The report primarily compares individuals in the same positions or tasks before evaluating individual performance. A distinguishing feature is the emphasis on ENA interaction during editorial meetings led by chefs.

The DND method proved easy to implement and perfectly suited to the use case of creating different strategies in a business environment. The method can be readily applied to the business and customized as needed without any constraints. Implementing the nudge context allowed strategies to be compared against objectives at any time, helping to assess potential impact. The method's ease of use allows it to be introduced to stakeholders or experts at any time.

4.3. Participatory workshop

A participatory workshop involving five participants, including two stakeholders and three experts, was conducted to engage stakeholders in the Nudge development process. Decisions were guided by the Nudge concept, with the workshop aiming to facilitate collaborative brainstorming among individuals with varying levels of involvement in ENA and the process. The workshop included a general brainstorming session and an introduction to nudging to familiarize participants with the topic and ensure a productive outcome. The goal was to develop technically and journalistically feasible strategies as well as to understand the current environment of ENA users and the desired state for the future. Stakeholders were able to share their impressions and tell the experts how the ENA is being used and what problems need to be solved. Common goals and metrics for success were defined, and an analysis

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was made of which current behaviors hinder these goals and which future behaviors can help achieve the goal. Facilitative and hindering elements of both Systems were defined to create a standardized picture of which elements can have an impact on the target group and their usage of ENA. Ideas were also generated on one hand to decimate unwanted behavior and on the other to reinforce desired behavior before strategies were compiled and refined.

Participants jointly designed strategies with the involvement of experts and stakeholders:

1. **Integrated Reward System with Feedback –** Including pop-up notifications of achievements, prompts to rate the ENA, and chat-based add-ons or messages from the bot.
2. **Community with Mentoring Support** – Incorporating a sense of community to enhance engagement with the ENA. Utilizing Google Space for community interactions and a messenger who is knowledgeable about the ENA and familiar with journalistic work (hybrid role).
3. **Impact Report** – Highlighting Consequences; Including feedback messages detailing consequences, delivered both as in-time prompts within notifications and through separate messages or reports.

When comparing the strategies developed in the workshop with the Digital Nudge Design Model, it is noteworthy that there are overlaps. As previously evidenced through the interviews, the staff at Ippen Digital places a clear emphasis on social interaction and incentives in the form of rewards and feedback to integrate daily use of the ENA into their workflow. Therefore, the workshop served to validate what was perceived through the encoding process of the interviews.

5. Discussion

The data collected during the study supports the theory that specific triggers can help influence the human decision-making process by relying on specific heuristics to help stem the tide of decisions made throughout the day. People often do not act rationally, primarily because much of our decision-making occurs in the automated part of the brain known as System 1, which functions unconsciously (Spreer, 2018). Especially design approaches like nudging, which relies on heuristics to change behavior, can be very effective in following routine processes and changing them (Thaler and Sunstein, 2008). In support of this, it has been demonstrated that strategies based on different biases and heuristics can be created and applied using existing models such as MINDSPACE (Dolan et al., 2012) or the Digital Nudge Design Method (Mirsch, Lehrer, et al., 2018).

Previous studies have explored the theory and concepts of behavioral design and nudging. However, this research takes a practical approach by developing a design strategy tailored to the ENA product initiative. By addressing the specific needs and frustrations of editors and the target users of ENA and proposing nudges tailored to their workflow and needs, this research provides practical recommendations for promoting behavior change and improving user engagement with augmented analytics.

By providing a comprehensive and user-centered design strategy that incorporates behavioral design principles and nudging techniques, this research adds to the existing body of knowledge. It provides a practical approach to addressing the hesitations and barriers that editors may have in using ENA. It also improves their experience with the tool. New insights into the problem were uncovered through this study‘s qualitative research and analysis. The research identified editors‘ specific needs and pain points. These included a desire for a tool that simplifies workflow, saves time, and improves article quality and revenue. The study identified several potential obstacles and concerns, including doubts about AI without human involvement, default settings, and anonymous performance monitoring in relation to the proposed design approach.

This study has significantly improved reader understanding by adopting a user-centered approach and involving experts and editors in the research process. It highlights the importance of understanding users‘ needs, addressing their concerns and barriers, and designing interventions aligned with their motivations and goals. Integrating behavioral science and design into the development of the ENA product initiative provides a practical framework for promoting the use of augmented analytics tools. It also provides recommendations for implementing nudges to drive behavior change without coercion.

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6. Conclusion

This work aimed to develop and evaluate nudge strategies based on behavioral science to improve the use of the analytics tool Editorial News Assistant (ENA) in the daily work of editors of the company Ippen Digital. The aim was to create a practical and actionable strategy to support using the ENA and improve user experience. The central research question posed and answered here was the following: “To what extent do digital nudging design approaches reduce cognitive load and promote behavioral change among editors towards the use of augmented analytics in their work processes, and how do these design approaches influence editors‘ perceptions and attitudes towards the use of these tools?”

Research demonstrates that conscious triggers can subconsciously influence decisions by relying on specific heuristics, an approach known as nudging, which fosters intrinsic motivation without patronizing individuals. There's a compelling need to extend these nudges into the digital realm, given the era of digitalization and the abundance of decision-making processes. This transition requires a user-centered approach to identify the most effective variables. The digital environment offers diverse possibilities for tailoring nudges, a process refined through iterative testing. This research aimed to gain insights into editors' behavior, bridging human psychology, analytics, and design to reveal the complexity of decision-making.

The study focused on aligning the user needs of editors with expert perspectives through qualitative in-house research and analysis. The aim was to enhance mutual understanding by investigating how experts and editors work with the ENA, addressing pain points, and improving user experience. The research yielded comprehensive strategies incorporating stakeholder and expert insights, featuring a mix of positive and negative connotative nudges. These strategies can promote greater ENA usage by editors, fostering sustainable improvement and linking its use with positive outcomes. It's essential to note that while this approach can be effective, there are alternative solutions to the issue at hand. These strategies have yet to be implemented and tested within the company to support the scientific findings with metrics. However, as ENA is not currently included in the Corporate OKRs, this will be done at a later stage.

Further (user) research is needed to refine nudge approaches, including personalization possibilities. Expanding the range of interviews and analyses to gather diverse qualitative data can better inform design decisions. Precisely addressing the needs of all user groups is crucial for developing effective solutions. Future studies should involve stakeholders more in the nudging design process, fostering a positive association with the ENA and addressing their concerns. This shift toward a more user-centric approach can enhance revenue, particularly from the work of the editors. The research has also strengthened collaboration across the company, enabling future projects and studies. By integrating insights from various fields, this research assists Ippen Digital in optimizing decision-making processes, improving workflow efficiency, and nurturing a data-driven work culture.

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